“AI-driven electronic customer relationship management and brand advocacy: The mediating role of consumption values in Vietnam’s digital banking sector”

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AI-DRIVEN ELECTRONIC CUSTOMER RELATIONSHIP MANAGEMENT AND BRAND ADVOCACY: THE MEDIATING ROLE OF CONSUMPTION VALUES IN VIETNAM'S DIGITAL BANKING SECTOR

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Abstract

The rapid adoption of artificial intelligence in digital banking is transforming how financial institutions manage customer relationships and encourage customer advocacy. However, empirical evidence explaining how artificial intelligence-driven electronic customer relationship management influences brand advocacy through different consumption values remains limited. This study aims to assess the effect of AI-driven electronic customer relationship management on brand advocacy and to examine the mediating roles of consumption values in Vietnam's digital banking context. A quantitative cross-sectional survey was conducted with 468 users of digital banking services who had interacted with artificial intelligence-enabled customer service functions, and the data were analyzed using partial least squares structural equation modelling. The results show that AI-driven electronic customer relationship management has a positive and statistically significant direct effect on brand advocacy ($\beta = 0.194$, $p < 0.001$). Functional value ($\beta = 0.092$, $p = 0.030$), monetary value ($\beta = 0.347$, $p < 0.001$), epistemic value ($\beta = 0.197$, $p < 0.001$), and social value ($\beta = 0.104$, $p = 0.010$) also positively influence brand advocacy, whereas emotional value does not have a significant effect ($\beta = 0.023$, $p = 0.703$). Monetary value emerges as the strongest predictor of brand advocacy, and the model explains 63.4% of the variance in this construct. The findings indicate that artificial intelligence-enabled relationship management systems strengthen brand advocacy primarily when they deliver tangible economic, informational, and functional benefits to digital banking customers.

Keywords personalization, predictive analytics, chatbot interaction, consumption value, word of mouth, customer engagement, fintech adoption, service automation

JEL Classification M31, G21, O33

INTRODUCTION

In the past decade, the banking sector has moved beyond basic process digitalization towards data-driven and algorithmic intelligence. Many financial institutions now embed artificial intelligence within their electronic customer relationship management systems (AI-driven ECRM) to analyze behavioral patterns, anticipate needs and tailor interactions in real time. This shift alters how banks construct value and sustains customer relationships, as financial recommendations become increasingly aligned with individual profiles. Some systems function efficiently. Others do not. Yet technological investment alone does not guarantee durable customer relationships. A technically advanced system may still fall short of generating deeper behavioral

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commitment. Digital banking intensifies this tension. Organizations seek not only continued service usage but also aspire to cultivate customers who voluntarily advocate for the brand. The challenge is clear. Understanding how technological capabilities translate into advocacy-related behavior becomes an essential line of inquiry.

The banking context introduces conditions that differ markedly from many other service domains. Financial decisions are closely tied to risk and demand a high degree of accuracy, so customers often weigh functional and economic benefits before forming an overall evaluation of a service. The pattern contrasts with research in retail or e-commerce, where emotion and experiential cues typically receive greater emphasis. The financial environment tends to operate under a more rational logic during assessment and decision-making. This makes it uncertain whether mechanisms identified in entertainment-oriented consumer sectors can be transferred directly to digital banking without empirical verification. Another issue emerges from the orientation of current fintech studies. Much of the existing work concentrates on acceptance or usage intentions, while brand advocacy reflects a more advanced relational outcome between customers and organizations. The gap is evident. Advocacy signifies a level of commitment that extends beyond continued use, and it requires a distinct explanatory approach.

In practice, AI-driven ECRM systems can generate several forms of customer value, including greater convenience during transactions, reduced financial costs, decision-making support and timely access to financial information. The extent to which each type of value contributes to brand-advocacy behavior in digital banking remains unclear, and the way these value dimensions mediate the influence of technology has not been fully established. The issue becomes more pronounced in emerging markets, where rapid digital transformation coincides with user behavior shaped by both utilitarian motives and contextual factors unique to these environments. Stemming from this, the present study concentrates on clarifying the mechanism through which AI-driven ECRM affects customer brand advocacy, drawing on the multidimensional structure of consumption values in Vietnam's digital banking context.

1. LITERATURE REVIEW AND HYPOTHESES

In the early phase of digital transformation, electronic customer relationship management systems (ECRM) mainly centered on process automation and customer-data administration to help firms monitor transactions and enhance marketing efficiency. Some tools worked well. Others showed clear limitations. The emergence of artificial intelligence has since altered the foundations of CRM, as AI-enabled systems increasingly operate as analytical and predictive engines for understanding customer behavior. Studies indicate that AI not only improves CRM processes but also shifts the relationship-management model from reactive responses to predictive capability through machine learning, data analytics and automated decision-support mechanisms (Libai et al., 2020; Ozay et al., 2024).

The shift towards CRM systems integrated with artificial intelligence carries particular significance in the digital-banking environment. Large-scale data-analysis capabilities enable banks to predict financial behavior and personalize services at scale (Munira, 2025). AI-based personalization does more than enhance user experience. It strengthens post-usage engagement, while real-time algorithms can reduce friction along the service journey and improve the operational efficiency of digital-banking platforms (Averineni et al., 2024; Gavade, 2024; Tran, 2024). Most existing studies continue to emphasize technical benefits or technology-acceptance intentions, yet the psychological processes that occur after adoption, namely how AI systems translate into behavioral commitments within customer relationships, remain insufficiently explored (Mokha & Kumar, 2022). The gap is notable in the banking sector, where financial decisions involve risk and require a high level of reliability. If technological improvement will automatically lead to durable loyalty risks oversimplifying the complexity of customer behavior. Accordingly, research efforts need to move beyond evaluating the technical performance of

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AI and shift towards explaining how technology generates value for customers and through which mechanisms these forms of value contribute to relational behavior.

Consumption Value Theory (CVT) developed by Sheth et al. (1991) offers a suitable analytical lens for explaining this mechanism. Under CVT, consumer behavior is shaped by five value components: functional, economic, emotional, epistemic and social value (Tuong et al., 2025). The theory highlights the multidimensional nature of customers' subjective assessments of products or services. In the digital-banking context, prior studies indicate that functional, epistemic and economic value play significant roles in encouraging continued use of mobile-banking services and mobile-payment systems (Karjaluoto et al., 2021; Omigie et al., 2017; Raman & Aashish, 2021). Perceived financial gains can also strengthen customer loyalty (Pal et al., 2021). Some earlier studies examined only one or two value components, yet such a one-dimensional approach may overlook emerging non-functional value mechanisms in digital-service environments (Ledro et al., 2022). For example, the novelty of technology may stimulate epistemic value (Palamidovska-Sterjadovska et al., 2024), while interactions with AI chatbots can generate social value and reinforce customer trust (Shahzad et al., 2024). These findings suggest that consumption value in AI-enabled services is inherently multidimensional. However, the direct integration between AI-driven ECRM and the five-component structure of CVT has not been fully tested.

In service marketing, loyalty is often assessed through repurchase intentions, yet many scholars argue that brand advocacy represents a higher level of relational commitment expressed through voluntary actions such as recommending, defending and disseminating positive representations of a brand (Wilk et al., 2020). The issue becomes more pronounced in fintech settings, where switching costs are low and cultivating a segment of active brand advocates becomes strategically important for competitive advantage (Surinder K Dhingra et al., 2025). A large share of AI- and CRM-related research still concentrates on outcome variables such as customer lifetime value, satisfaction or trust, while empirical evidence on voluntary social behaviors, such as brand advocacy, within digital banking remains limited. Some studies do indicate that technological features, including AI anthropomorphism, can stimulate engagement and online word-of-mouth (McLean et al., 2021). The evidence, however, is still fragmented.

In Vietnam, several recent studies have broadened the understanding of CRM in the banking sector through the SCRM framework. Thach et al. (2025a) show that SCRM exerts a positive influence on customer lifetime value and is shaped by technological, organizational and environmental factors. Thach et al. (2025b) further clarify the mediating role of engagement within this relationship. AI-driven ECRM, however, differs from socially oriented SCRM. It operates through prediction and automated decision-making, signaling a shift from interaction-based CRM towards forecast-based CRM.

Accordingly, although research on CRM in the banking sector has advanced considerably, three gaps remain. One concerns the lack of distinction between socially driven CRM systems and AI-based predictive CRM. The second relates to the emphasis of prior studies on behavioral outcomes such as satisfaction or loyalty, while brand advocacy reflects a more elevated level of relational commitment. The third involves the limited examination of the mediating role of the multidimensional consumption-value structure in the context of AI-driven ECRM.

The purpose of this study is to assess the influence of AI-driven ECRM on brand advocacy through the mediating role of five consumption-value components within Vietnam's digital-banking environment.

According to the logic of the S-O-R framework, AI-driven ECRM can be viewed as a technological stimulus that shapes customers' internal evaluations of service value, which subsequently give rise to behavioral responses. When customers perceive that AI systems help them execute transactions more quickly and with greater accuracy, the functional value of the service becomes reinforced (Munira, 2025). Predictive algorithms may also optimize financial choices

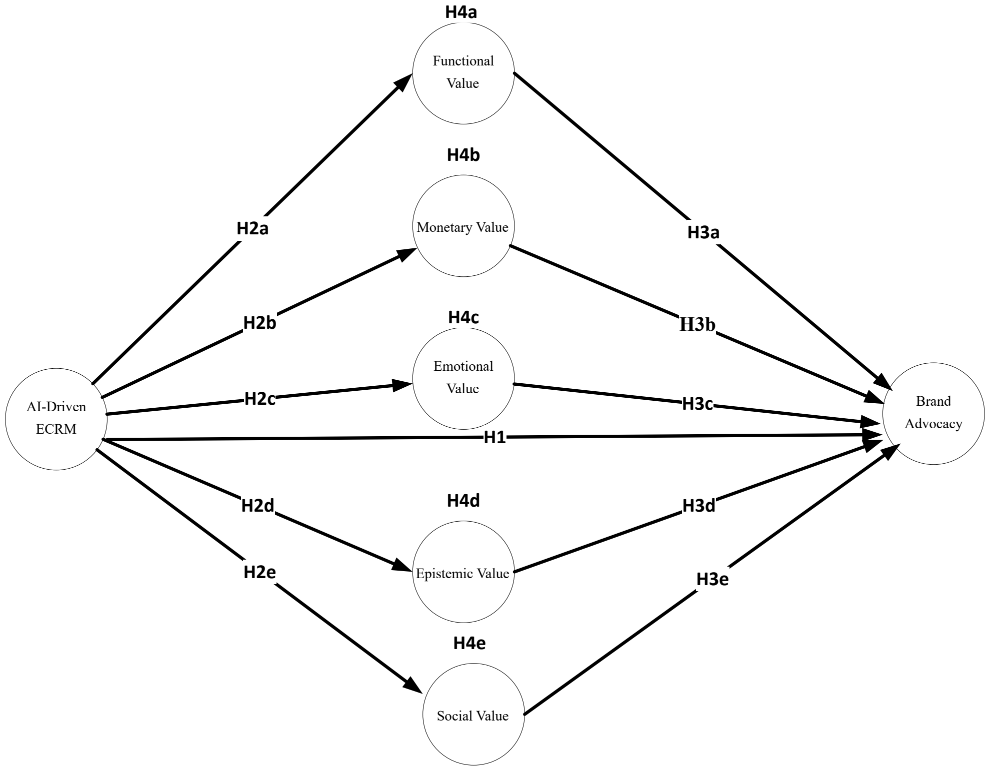

Figure 1. Proposed research model

and generate clear economic benefits for customers (Akter et al., 2025; Haftor et al., 2024). The ability of AI to personalize interactions and respond flexibly can create a sense of reassurance and reduce tension during financial decision-making (Alagarsamy & Mehrolia, 2023; Park & Lee, 2024). Besides, data-driven information and recommendations help customers understand financial products more clearly and stimulate epistemic value (Libai et al., 2020; Tran, 2024).

In digital consumption settings, engaging with banking services that integrate advanced technologies can also enhance individuals' modern self-image and generate social value (Flavián et al., 2024).

According to CVT, these value components play an important role in shaping customers' post-usage behavior. Functional and economic value can increase the likelihood that customers recommend services to others (Ranaweera & Karjaluoto, 2017). Epistemic value encourages the sharing of useful information within user communities (Nadeem et al., 2021). Social and emotional value, in turn, can reinforce motivations for self-expression and support the maintenance of a positive self-image through favorable word-of-mouth behavior (Rather et al., 2022). Consequently, consumption values are expected to act as a bridge between AI-driven ECRM and brand-advocacy behavior.

Prior studies show that CRM systems enhanced with artificial intelligence can markedly improve firm-customer interactions through service personalization and predictive analytics. Evidence, however, remains limited regarding how this technology translates into higher-order behavioral commitments within digital banking. Building on the S-O-R framework and CVT, the present study proposes a model in which AI-driven ECRM exerts a direct effect on brand advocacy and an indirect effect through multidimensional consumption values.

Accordingly, the research hypotheses are formulated as follows:

H1: AI-driven ECRM has a positive effect on brand advocacy.

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H2: *AI-driven ECRM positively influences the components of consumption value, including (a) Functional Value, (b) Monetary Value, (c) Emotional Value, (d) Epistemic Value and (e) Social Value.*

H3: *The components of consumption value positively influence brand advocacy, including (a) Functional Value, (b) Monetary Value, (c) Emotional Value, (d) Epistemic Value and (e) Social Value.*

H4: *The components of consumption value mediate the relationship between AI-driven ECRM and Brand Advocacy, including (a) Functional Value, (b) Monetary Value, (c) Emotional Value, (d) Epistemic Value and (e) Social Value.*

2. METHODOLOGY

The study employed a quantitative design with a cross-sectional survey to examine the theoretical model linking AI-driven ECRM, consumption values and brand advocacy within Vietnam's digital-banking context. Data were collected through an online questionnaire administered via Google Forms in December 2025. The target population consisted of users of digital-banking services who had interacted with AI-supported functions in customer service. Most responses were gathered through Zalo, using a non-probability sampling strategy that combined convenience sampling and snowball sampling. Each participant confirmed that they had engaged with AI-enabled features, such as chatbots, virtual assistants or automated financial recommendations, within the previous six months.

Because the questionnaire was administered through Google Forms with mandatory-response settings, missing data were not present. However, responses showing extremely short completion times or patterned answering behavior were excluded to ensure data quality. The final dataset included 468 valid responses, which satisfies recommended sample-size requirements for PLS-SEM analysis (Sarstedt et al., 2022).

Table 1. Research sample structure (n = 468)

Variables	n	%
Gender	468	
Male	146	31.20%
Female	322	68.80%
Demographic age	468	
18-25	254	54.27%
26-35	121	25.85%
36-50	54	11.54%
≥50	39	8.33%
Education	468	
High school and below	41	8.76%
Vocational training or associate degree	14	2.99%
Undergraduate degree	367	78.42%
Master or Doctorate	46	9.83%
Occupation	468	
Student	165	35.26%
Self-employment	43	9.19%
Working in the private sector	112	23.93%
Working in the public sector	131	27.99%
Other	17	3.63%
Income (million VND)	468	
Less than 5 million VND	99	21.15%
Between 5 and less than10 million VND	85	18.16%
Between 10 and less than 20 million VND	118	25.21%
Above 20 million VND	166	35.47%

Table 1 presents the demographic characteristics of the research sample. Among 468 participants, women accounted for 68.8% and men for 31.2%. The majority fell within the 18-25 age group (54.27%), followed by those aged 26-35 (25.85%). Regarding educational attainment, most respondents held an undergraduate degree (78.42%). Students formed the largest occupational group (35.26%), followed by individuals working in the public and private sectors. More than half reported a monthly income of at least 10 million VND, indicating that the sample includes a substantial proportion of customers with regular access to digital-banking services.

The variables and measurement scales were adapted from prior studies to ensure alignment with the research context. The AI-driven ECRM construct was measured using items that capture the system's predictive capability, automated responses and its ability to interpret customer needs within the ECRM environment (Al-Dmour et al., 2019; Singh et al., 2023). The consumption-value components were operationalized following the framework proposed by Sheth et al. (1991), including functional and epistemic value (Karjaluoto et al., 2021), social value (Omigie et al., 2017; Raman & Aashish, 2021), emotional value (Tuong et al., 2025; Wong et al., 2018) and monetary value (Pal et al., 2021; Tuong et al., 2025). Brand advocacy was measured using a four-item scale capturing customers' willingness to recommend, promote, and defend the bank brand. The items were adapted from prior brand advocacy literature (Sweeney et al., 2020; Wilk et al., 2020). All items were measured on a five-point Likert scale ranging from "strongly disagree" to "strongly agree".

The questionnaire was translated from English into Vietnamese using the back-translation procedure (Brislin, 1970) to ensure semantic equivalence. The instrument was subsequently reviewed by four banking practitioners and one marketing lecturer to assess clarity and contextual relevance. Minor revisions were made based on their feedback. A pilot test with 30 digital banking users was then conducted to evaluate item comprehension and questionnaire flow, resulting in small wording adjustments prior to the main survey.

The data were analyzed using SmartPLS 4 following the two-stage procedure of PLS-SEM. The measurement model was assessed first through reliability, convergent validity and discriminant validity of the latent constructs. The structural model was then evaluated to test the hypotheses and estimate the effects of AI-driven ECRM and the consumption-value components on brand advocacy.

3. RESULTS

The study employed partial least squares structural equation modelling (PLS-SEM) to analyze the data, using SmartPLS 4.0 for estimation. The research team implemented a two-stage analytical procedure that comprised the assessment of the measurement model and the evaluation of the structural model, aiming to test the proposed hypotheses (Sarstedt et al., 2022).

Table 2 summarizes the results of the reliability and convergent-validity assessments of the measurement scales. The authors examined the measurement model through outer loadings, internal consistency reliability and convergent validity. The outer loadings for all indicators ranged from 0.753 to 0.893 and exceeded the 0.70 threshold, indicating that each item adequately reflected its corresponding latent construct. Cronbach's Alpha values fell between 0.776 and 0.867, while Composite Reliability (CR) values ranged from 0.863 to 0.909. These results demonstrate high internal consistency across all constructs and show no indication of item redundancy.

Besides, the AVE values of the constructs ranged from 0.613 to 0.764, exceeding the minimum threshold of 0.50, which indicates that each construct captured a substantial proportion of variance in its indicators. The VIF values for all items were below 3.3, ranging from 1.479 to 2.422, suggesting no serious multicollinearity issues within the model. Taken together, the measurement model met the required standards of reliability and convergent validity, allowing the analysis to proceed to the assessment of discriminant validity and the structural model.

Next, Table 3 presents the results of the discriminant-validity assessment across the research constructs using the HTMT criterion. Following the recommendation of Henseler et al. (2015), HTMT values should remain below 0.90 to ensure that latent constructs exhibit adequate discriminant validity. The results in Table 3 show that most construct pairs fall below this threshold. The values range from 0.573 to 0.885. The relationship between MOVA and BRAD reaches 0.885, which is the highest value in the model, yet still within the acceptable limit. Similarly, the pair consisting of AIDE and MOVA has an HTMT value of 0.849, while the pair involving EPVA and BRAD reaches 0.839.

Several values approach the 0.85 level, but all remain comfortably below the 0.90 boundary, indicating that the constructs retain sufficient discriminant power. No construct pair exceeds the allowable range, suggesting that there is no serious conceptual overlap in the model.

After confirming that the measurement model met the required standards of reliability and validity, the research team proceeded to evaluate the structural model using a bootstrapping technique with 5,000 resamples. The hypothesis-testing results are presented in Table 4. The findings indicate

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Table 2. Measurement model assessment

Constructs	Items	Outer loadings	Cronbach's Alpha	CR	AVE	VIF
AI-driven ECRM	AIDE		0.808	0.874	0.635	
	AIDE1	0.799				1.820
	AIDE2	0.831				1.901
	AIDE3	0.802				1.768
	AIDE4	0.753				1.610
Brand Advocacy	BRAD		0.813	0.877	0.641	
	BRAD1	0.757				1.479
	BRAD2	0.837				1.885
	BRAD3	0.786				1.736
	BRAD4	0.819				1.841
Emotional Value	EMVA		0.867	0.909	0.715	
	EMVA1	0.825				1.982
	EMVA2	0.850				2.029
	EMVA3	0.872				2.287
	EMVA4	0.836				2.019
Epistemic Value	EPVA		0.776	0.870	0.692	
	EPVA1	0.799				1.502
	EPVA2	0.866				1.859
	EPVA3	0.828				1.608
Functional Value	FUVA		0.789	0.863	0.613	
	FUVA1	0.779				1.560
	FUVA2	0.810				1.766
	FUVA3	0.778				1.565
	FUVA4	0.763				1.549
Monetary Value	MOVA		0.841	0.904	0.759	
	MOVA1	0.849				1.808
	MOVA2	0.878				2.080
	MOVA3	0.885				2.190
Social Value	SOVA		0.845	0.906	0.764	
	SOVA1	0.843				1.718
	SOVA2	0.893				2.422
	SOVA3	0.885				2.318

Table 3. Discriminant validity assessment using the HTMT criterion

	AIDE	BRAD	EMVA	EPVA	FUVA	MOVA	SOVA
AIDE							
BRAD	0.841						
EMVA	0.727	0.719					
EPVA	0.798	0.839	0.767				
FUVA	0.648	0.683	0.754	0.646			
MOVA	0.849	0.885	0.796	0.835	0.666		
SOVA	0.726	0.684	0.573	0.669	0.641	0.626	

that AI-driven ECRM (AIDE) exerts a direct and statistically significant effect on Brand Advocacy (BRAD) ($\beta = 0.194$; $p < 0.001$). Accordingly, hypothesis H1 is supported.

Regarding the effects of AIDE on the five components of consumption value, the results show that all relationships are statistically significant at $p < 0.001$. AIDE positively influences Functional Value ($\beta = 0.479$), Monetary Value ($\beta = 0.701$), Emotional Value ($\beta = 0.614$), Epistemic Value ($\beta = 0.633$), and Social Value ($\beta = 0.599$). Consequently, hypotheses *H2a*, *H2b*, *H2c*, *H2d* and *H2e* are all supported. Among these, MOVA demonstrates the strongest effect.

Considering the effects of consumption values on BRAD, the results show that FUVA ($\beta = 0.092$; p

Table 4. Hypotheses testing

Hypothesis	Path coefficient	Standard deviation (STDEV)	t-statistics (|O/STDEV|)	p-values	Results
Direct effects					
H1: AIDE → BRAD	0.194	0.054	3.602	0.000	Supported
H2a: AIDE → FUVA	0.479	0.040	11.873	0.000	Supported
H2b: AIDE → MOVA	0.701	0.026	26.692	0.000	Supported
H2c: AIDE → EMVA	0.614	0.034	18.236	0.000	Supported
H2d: AIDE → EPVA	0.633	0.036	17.644	0.000	Supported
H2e: AIDE → SOVA	0.599	0.032	18.480	0.000	Supported
H3a: FUVA → BRAD	0.092	0.042	2.167	0.030	Supported
H3b: MOVA → BRAD	0.347	0.055	6.341	0.000	Supported
H3c: EMVA → BRAD	0.023	0.059	0.382	0.703	Rejected
H3d: EPVA → BRAD	0.197	0.051	3.855	0.000	Supported
H3e: SOVA → BRAD	0.104	0.041	2.569	0.010	Supported
Multiple indirect effects					
H4a: AIDE → FUVA → BRAD	0.044	0.021	2.084	0.037	Supported
H4b: AIDE → MOVA → BRAD	0.244	0.041	6.009	0.000	Supported
H4c: AIDE → EMVA → BRAD	0.014	0.037	0.379	0.704	Rejected
H4d: AIDE → EPVA → BRAD	0.125	0.033	3.823	0.000	Supported
H4e: AIDE → SOVA → BRAD	0.062	0.025	2.525	0.012	Supported

Note: Adjusted R2: R2BRAD = 0.634; R2EMVA = 0.376, R2EPVA = 0.399, R2FUVA = 0.288; R2MOVA = 0.491, R2SOVA = 0.358. f2: f2AIDE → BRAD= 0.042; f2AIDE → EMVA= 0.605; f2AIDE → EPVA= 0.667; f2AIDE → FUVA= 0.298; f2AIDE → MOVA= 0.968; f2AIDE → SOVA= 0.561; f2 EMVA → BRAD= 0.001; f2 EPVA → BRAD= 0.048; f2FUVA → BRAD= 0.014; f2MOVA → BRAD= 0.123; f2SOVA → BRAD= 0.017; Q2: Q2BRAD = 0.395; Q2EMVA = 0.264, Q2EPVA = 0.274; Q2FUVA = 0.160; Q2MOVA = 0.368, Q2SOVA = 0.270.

= 0.030), MOVA (β = 0.347; $p < 0.001$), EPVA (β = 0.197; $p < 0.001$), and SOVA (β = 0.104; p = 0.010), all exert positive and statistically significant influences. Consequently, hypotheses *H3a*, *H3b*, *H3d* and *H3e* are supported. Conversely, EMVA does not exert a meaningful effect on BRAD (β = 0.023; p = 0.703), leading to the rejection of hypothesis *H3c*.

The analysis of indirect effects indicates that AIDE influences BRAD through FUVA (β = 0.044; p = 0.037), MOVA (β = 0.244; $p < 0.001$), EPVA (β = 0.125; $p < 0.001$), and SOVA (β = 0.062; p = 0.012). Accordingly, hypotheses *H4a*, *H4b*, *H4d* and *H4e* are supported. The indirect effect transmitted through EMVA is not statistically significant (β = 0.014; p = 0.704), resulting in the rejection of hypothesis *H4c*. Because the direct effect of AIDE on BRAD remains significant when the mediators are added to the model, FUVA, MOVA, EPVA and SOVA can be interpreted as partial mediators.

The adjusted R^2 value indicates that the model explains 63.4% of the variance in BRAD. The mediating variables account for levels of explained variance ranging from 28.8% to 49.1%. The effect-size analysis shows that AIDE has particularly strong effects on MOVA and EPVA, while MOVA emerges as the most influential predictor of BRAD. All Q^2 values exceed zero, confirming the predictive capability of the model.

4. DISCUSSION

The empirical results show strong support for the proposed theoretical model and offer several insights with academic and practical relevance.

Notably, AI-driven ECRM exerts a direct and positive influence on Brand Advocacy. This finding aligns with the logic of the S-O-R framework, in which technological factors act as external stimuli capable of triggering higher-order behavioral responses. The result extends earlier research that largely concentrated on usage intention or satisfaction (Karjaluoto et al., 2021; Omigie et al., 2017) by demonstrating that AI-enabled systems do more than maintain relationships; they also activate socially oriented advocacy behaviors. In contrast to studies on SCRM in Vietnam (Thach et al., 2025a; Thach et al., 2025b), where engagement

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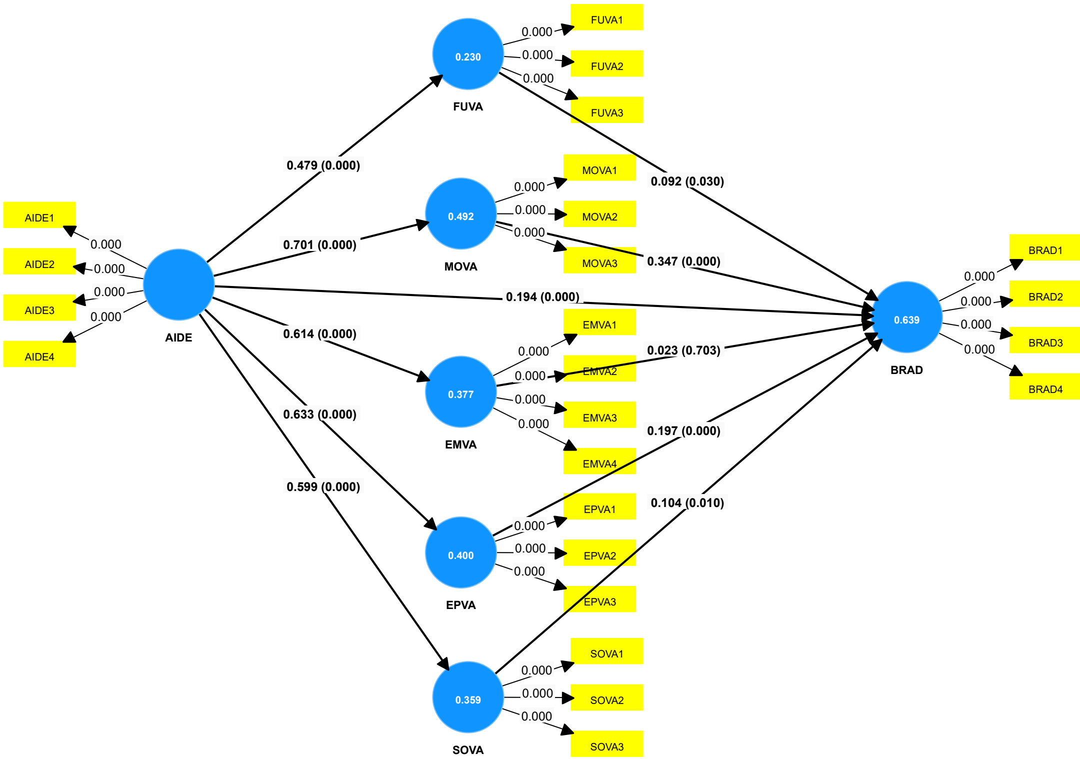

Figure 2. Structural model results

functions as the primary mediator, the present research indicates that consumption values constitute the central bridging mechanism in AI-based predictive ECRM environments.

Secondly, AI-driven ECRM exerts significant effects on all five components of consumption value. This result reinforces the Consumption Value Theory proposed by Sheth et al. (1991) and confirms that AI technologies generate not only functional benefits but also stimulate cognitive and social evaluations. The finding aligns with the argument of Libai et al. (2020), who explain that AI reshapes how firms create relational value through large-scale prediction and personalization. The result is also consistent with Karjaluoto et al. (2021), who report that functional and epistemic value play an important role in digital-banking services.

However, the most noteworthy contribution of the study lies in identifying the relative partial mediating role of each value component. Monetary Value emerges as the strongest partial mediating mechanism between AI-driven ECRM and Brand Advocacy. The pattern indicates that digital-banking customers prioritize tangible economic benefits such as reduced costs, optimized interest returns and personalized financial recommendations. This finding aligns with Pal et al. (2021), who demonstrate that mobile-payment services generate value by optimizing net financial benefits. It also reflects the specific nature of the financial sector, where consumption decisions are closely tied to cost-benefit assessments and perceived levels of risk.

Epistemic Value and Functional Value also serve as notable mediating mechanisms. This pattern suggests that AI-driven ECRM strengthens customers' sense of informational control and transaction efficiency, which in turn reinforces their motivation to recommend and defend the brand. The result aligns with Raman and Aashish (2021), who found that perceived usefulness and convenience stimulate continued usage of mobile-payment systems. The present study extends this line of reasoning by demonstrating that these values do more than encourage repeated usage; they also activate proactive advocacy behavior.

Conversely, Emotional Value does not exert a meaningful influence on Brand Advocacy and does not function as a mediating factor. This finding contrasts with several studies in digital retail or e-commerce, where effective and experiential elements often play a prominent role (Rather et al., 2022). Divergence may stem from the distinctive characteristics of the digital-banking context. Financial decisions involve risk and require a high degree of accuracy, prompting customers to prioritize stability and tangible benefits over purely positive emotional responses. AI-driven ECRM systems in banking operate primarily through predictive and optimization algorithms, generating fewer symbolic or affect-laden experiences than those typically found in retail or entertainment settings. Accordingly, the non-significant role of Emotional Value does not weaken the model; instead, it reflects the value structure specific to digital financial services.

The results concerning the partial mediating roles of the value components also provide evidence supporting the argument of Mokha and Kumar (2022), who suggest that technology influences behavior only through the process in which customers internalize it as specific perceived values. AI-driven ECRM does not generate advocacy behavior in a mechanical manner. Instead, customers convert technological capabilities into value assessments, and these assessments give rise to voluntary social behavior.

From a theoretical perspective, the study contributes along three main directions. It extends the application of the S-O-R framework in digital-banking research by incorporating the multidimensional consumption-value structure as the "organism" component. It also differentiates clearly between socially oriented CRM and AI-based predictive ECRM, thereby clarifying the distinct mechanisms through which each approach generates value. Besides, the study shifts the analytical focus from loyalty or repurchase intention towards brand advocacy, which represents a higher and more socially embedded form of relational commitment.

Even so, the study still contains several limitations. The data were collected using a cross-sectional design, which prevents the analysis from capturing changes that may unfold over time. The model also does not account for potential moderating variables such as technology trust, levels of digital-financial literacy or individual cultural orientations. Future research could extend the model by incorporating trust or perceived risk as moderators. A comparison between traditional banks and digital-only banks may also help clarify the relative role of Emotional Value across different organizational structures.

In summary, the study demonstrates that AI-driven ECRM promotes Brand Advocacy primarily through rational value mechanisms, particularly Monetary Value and Epistemic Value. This insight contributes to a clearer understanding of how AI technologies shape customer behavior in digital banking and expands the theoretical foundation of consumption value in intelligent-service environments.

CONCLUSION

This study was designed to examine the influence of AI-driven ECRM on Brand Advocacy in Vietnam's digital-banking sector, while clarifying the mediating role of the five consumption-value components defined within the Consumption Value Theory framework. Using PLS-SEM analysis with 468 valid observations, the empirical results demonstrate that AI-driven ECRM not only exerts a direct effect on advocacy behavior but also shapes it indirectly through specific value mechanisms.

The findings indicate that AI-driven ECRM has a positive impact on all five consumption-value components. The magnitude of these effects, however, is not uniform, with Monetary Value demonstrating the strongest influence. Monetary Value emerges as the strongest mediating mechanism, followed by Epistemic Value, Social Value, and Functional Value. In contrast, Emotional Value shows no meaningful influence on Brand Advocacy and does not mediate any relationship within the model. These results suggest that in the digital-banking environment, where financial decisions are closely associated with risk and cost-benefit considerations, customers prioritize rational value assessments over purely affective factors.

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Stemming from these findings, three core implications emerge. The first concerns the potential for AI-driven ECRM to generate durable relational advantages when the system enables customers to recognize clear economic benefits and strengthens their capacity for financial decision-making. The second relates to the role of the consumption-value structure, which operates as the central mechanism through which technological capabilities are translated into brand-advocacy behavior. Consequently, the effectiveness of AI depends not only on its technical sophistication but also on the way customers internalize the value it provides. The third implication reflects the rational nature of advocacy formation in Vietnam's digital-banking environment, suggesting that technology strategies should prioritize the optimization of economic and cognitive value rather than focusing solely on enhancing emotional experiences.

Overall, the study provides empirical evidence showing that AI-driven ECRM can become a strategic foundation for cultivating a segment of active brand advocates when it is implemented in ways that enhance specific perceived values. The findings clarify the mechanisms through which artificial intelligence operates within digital-banking services and extend current understanding of how consumption values shape higher-order behavioral outcomes such as brand advocacy.

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APPENDIX A

Table A1. Measurement items

Constructs	No.	Items
AI-driven ECRM	AIDE	Al-Dmour et al. (2019), Singh et al. (2023)
	AIDE1	AI-Driven ECRM personalizes customer interactions based on individual data and preferences.
	AIDE2	AI-Driven ECRM enhances customer satisfaction through timely and relevant interactions.
	AIDE3	AI-Driven ECRM strengthens customer relationships by offering continuous feedback.
	AIDE4	AI-Driven ECRM improves customer retention by offering tailored services and support.
Functional Value	FUVA	Karjaluoto et al. (2021)
	FUVA1	Notifications and services provided through AI-Driven ECRM help me save time when conducting banking transactions.
	FUVA2	AI-Driven ECRM allows me to handle requests and issues easily and quickly.
	FUVA3	I believe AI-Driven ECRM helps me manage my personal finances more effectively.
	FUVA4	I feel that my information and data are secure when interacting through AI-Driven ECRM
Monetary Value	MOVA	Tuong et al. (2025), Pal et al. (2021)
	MOVA1	I save costs when using banking services through AI-Driven ECRM.
	MOVA2	AI-Driven ECRM enables me to receive reward schemes, cashback or gifts that align with my personal needs.
	MOVA3	I feel that using AI-Driven ECRM provides higher economic value compared with traditional channels.
Emotional Value	EMVA	Tuong et al. (2025), Wong et al. (2018)
	EMVA1	I feel comfortable and at ease when interacting with the bank's AI-Driven ECRM system.
	EMVA2	I feel personally cared for when receiving information through AI-Driven ECRM.
	EMVA3	Interactions from AI-Driven ECRM make me feel more confident in the bank.
	EMVA4	I am satisfied when the bank responds promptly and courteously through AI-Driven ECRM.
Epistemic Value	EPVA	Karjaluoto et al. (2021)
	EPVA1	I find it interesting to explore new features of the AI-Driven ECRM system.
	EPVA2	I am often curious about how AI-Driven ECRM personalizes the experience for me.
	EPVA3	I enjoy seeing the bank apply new technologies (AI, chatbots, data analytics) in AI-Driven ECRM
Social Value	SOVA	Omigie et al. (2017), Raman and Aashish (2021)
	SOVA1	Using AI-Driven ECRM channels (such as apps, email or chatbots) makes me feel modern and technologically competent.
	SOVA2	I perceive my bank as highly regarded because it offers a professional and user-friendly AI-Driven ECRM system.
	SOVA3	Interacting via AI-Driven ECRM helps me share information easily and stay connected with the bank's user community.
Brand Advocacy	BRAD	Wilk et al. (2020), Sweeney et al. (2020)
	BRAD1	I would actively recommend this bank's digital banking services to other people.
	BRAD2	I would say positive things about this bank when discussing digital banking services with others.
	BRAD3	I would encourage other people to use this bank's digital banking services.
	BRAD4	I would defend this bank if other people criticized it unfairly.

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