“The impact of artificial intelligence (AI) application on marketing performance in small and medium-sized enterprises in Hanoi”

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THE IMPACT OF ARTIFICIAL INTELLIGENCE (AI) APPLICATION ON MARKETING PERFORMANCE IN SMALL AND MEDIUM-SIZED ENTERPRISES IN HANOI

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Abstract

The rapid development of artificial intelligence (AI) and digital transformation has significantly reshaped marketing activities, particularly for small and medium-sized enterprises (SMEs) operating under resource constraints. In emerging economies such as Vietnam, empirical evidence regarding the effectiveness of AI application in marketing remains limited and fragmented. Therefore, this study aims to examine the impact of AI application on marketing performance of SMEs in Hanoi, Vietnam. The study applies the resource-based view (RBV) and dynamic capabilities theory (DCT) as the theoretical foundation to analyze the relationships between AI-enabled marketing capabilities and marketing performance. The study used quantitative research through a survey of 237 SME managers and employees in Hanoi. The collected data were analyzed using SPSS and structural equation modeling (SEM).

The findings indicate that AI application in customer data analytics positively affects market performance ($\beta = 0.219$, $p < 0.01$), customer performance ($\beta = 0.186$, $p < 0.05$), financial performance ($\beta = 0.174$, $p = 0.050$), and communication performance ($\beta = 0.620$, $p < 0.001$). AI-enabled marketing personalization is positively associated with market, financial, and communication performance. However, customer performance showed a statistically significant negative coefficient. In addition, AI-based marketing automation and interactive customer communication demonstrate varying effects across different dimensions of marketing performance. The study contributes to the literature on AI-driven marketing by providing empirical evidence from an emerging economy context and offering managerial implications for SMEs seeking to improve marketing effectiveness through AI adoption.

Keywords artificial intelligence, AI-enabled marketing, marketing performance, SMEs, customer analytics, marketing personalization, marketing automation, Vietnam

JEL Classification M31, O33, L26

INTRODUCTION

Amid the Fourth Industrial Revolution and rapid digital transformation, artificial intelligence (AI) is increasingly recognized as a strategic resource in business marketing. The proliferation of big data, digital platforms, and advanced analytics has fundamentally transformed the way firms design, implement, and evaluate marketing activities. AI enables businesses to enhance customer data analytics, personalize marketing activities, automate marketing processes, and improve customer experience, thereby significantly increasing marketing effectiveness and operational efficiency (Wedel & Kannan, 2016; Davenport & Ronanki, 2018; Huang & Rust, 2021). From the perspective of dynamic capability theory, AI is a critical tool that supports firms in sensing market changes, seizing emerging opportunities, and reconfiguring resources to sustain competitive advantage in highly dynamic environments (Teece et al., 2008; Teece, 2007).

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This issue is particularly relevant to small and medium-sized enterprises. Compared with large firms, SMEs generally operate with more limited financial, technological, and human resources. AI may therefore allow them to improve marketing productivity and respond more rapidly to market changes. At the same time, resource constraints, limited digital maturity, fragmented customer data, and insufficient implementation capabilities may prevent SMEs from obtaining consistent benefits from AI adoption (Kaplan & Haenlein, 2019; Rust, 2020).

Existing discussions frequently approach AI adoption as a broad technological or organizational phenomenon. Such an aggregated perspective may conceal substantial differences between customer data analytics, marketing personalization, marketing automation, and AI-enabled customer interaction. It also offers limited explanation of why a particular AI application may improve one dimension of marketing performance but have little or even an unexpected association with another.

The core scientific problem is therefore not simply whether AI improves marketing performance, but how distinct AI-enabled marketing applications are associated with different performance outcomes in resource-constrained SMEs. This issue is especially relevant in emerging-market settings such as Vietnam, where AI adoption is increasing but organizational readiness and implementation conditions remain uneven.

1. LITERATURE REVIEW

1.1. Theoretical basis

The resource-based view (RBV) theory posits that a company's operational efficiency and competitive advantage depend on its ability to possess and exploit valuable, rare, inimitable, and irreplaceable endogenous resources (Barney, 1991). In a digital economy, the application of artificial intelligence (AI) in marketing helps small and medium-sized enterprises (SMEs) transform technology, data, and customer knowledge into strategic intangible resources, meeting VRIN criteria and creating sustainable value (Barney et al., 2011). Particularly for SMEs, AI contributes to optimizing the use of limited resources, improving the accuracy of marketing decisions, and enhancing market access efficiency, customer satisfaction, and financial results (Morgan et al., 2009).

The dynamic capability theory (DCT) provides a suitable theoretical framework for explaining how applying artificial intelligence (AI) in marketing can help SMEs improve operational efficiency in a volatile business environment. DCT emphasizes the ability of businesses to perceive market opportunities and challenges, seize opportunities, and reconfigure resources to adapt to a rapidly changing competitive environment (Teece et al., 2008).

Artificial intelligence is understood as a field of computer science focused on developing systems capable of performing tasks requiring human intelligence, including learning, reasoning, perception, and decision-making. AI allows machines to simulate cognitive processes through data, algorithms, and computational power, thereby assisting or replacing humans in many complex activities (Kaplan & Haenlein, 2019). In the modern business context, AI is not just seen as a single technology but as a collection of technologies such as machine learning, deep learning, natural language processing, and computer vision, enabling systems to continuously learn from data and improve performance over time (Huang & Rust, 2021).

Marketing performance reflects the extent to which marketing activities contribute to achieving business objectives and is increasingly approached as a multidimensional concept, not limited to financial indicators but also encompassing market, customer, and communication outcomes (Clark, 1999; Morgan et al., 2009). This approach emphasizes the role of marketing in creating value for customers, building a competitive position, and maintaining long-term customer relationships, thereby indirectly impacting financial results (Rust et al., 2004). In digital marketing, marketing performance is also demonstrated through communication effectiveness and the level of interaction with customers, contributing to sustainable improvements in market and customer effectiveness.

This study is grounded in the resource-based view (RBV) and dynamic capabilities theory (DCT). The resource-based view and dynamic capabilities theory provide complementary explanations of how AI may contribute to marketing performance. From an RBV perspective, commercially available AI technologies alone are unlikely to constitute rare or inimitable resources. Their strategic value emerges when they are combined with firm-specific customer data, employee expertise, organizational routines, and accumulated market knowledge. Competitors may find these resource combinations difficult to replicate because firms develop them through firm-specific learning and integration processes. DCT further explains how these resources are mobilized under changing market conditions. AI-enabled customer data analytics primarily strengthens sensing capabilities by identifying customer patterns, emerging preferences, and changes in demand. Marketing personalization and automation support seizing capabilities by enabling firms to convert identified opportunities into targeted offers, campaigns, and scalable marketing actions. AI-enabled communication and customer interaction may reconfigure capabilities by reshaping customer service routines, communication channels, and engagement processes.

The two perspectives are therefore related but conceptually distinct. RBV explains the strategic value of the underlying resource configuration, whereas DCT explains how firms deploy and reconfigure those resources to respond to market change. Importantly, access to an AI tool does not necessarily generate superior performance. Performance benefits depend on the quality of firm-specific data, complementary human skills, organizational integration, and the ability to translate AI-generated insights into marketing actions. This integrated perspective also suggests that different AI applications may not generate uniform outcomes. Analytics may primarily improve informational accuracy and market sensing, personalization may increase relevance but also create implementation risks, automation may enhance process efficiency without immediately generating financial returns, and AI-supported interaction may improve engagement without necessarily expanding market share.

Although existing studies have examined AI in marketing, three major gaps remain. First, most studies focus on developed economies, limiting generalizability to emerging markets such as Vietnam. Second, AI is often examined as a single construct rather than as a set of distinct functional capabilities. Third, there is limited empirical evidence on how different AI applications influence multiple dimensions of marketing performance in SMEs.

Therefore, there is a need for an integrated empirical model that examines the multidimensional effects of AI applications on marketing performance in SMEs within emerging economies. This study addresses these gaps by investigating four key AI dimensions customer data analytics, marketing personalization, marketing automation, and customer interaction and their effects on four dimensions of marketing performance in SMEs in Hanoi, Vietnam.

1.2. Research hypotheses

The research hypotheses aim to empirically test the effects of applying AI dimensions, including customer data analytics, marketing personalization, marketing automation, and communication and customer interaction, on marketing performance, including market, customer, financial, and communication performance. Through these hypotheses, the study examines whether different AI models generate distinct performance outcomes among SMEs in Hanoi, Vietnam.

The application of artificial intelligence (AI) in customer data analysis helps businesses improve their ability to collect, process, and exploit data, thereby supporting data-driven marketing decision-making instead of experience-driven decision-making (Davenport et al., 2020; Huang & Rust, 2021). A better understanding of customer behavior and needs helps businesses reach target markets, personalize marketing activities, optimize costs, and improve communication effectiveness, thereby positively affecting market performance, customer performance, and financial per-

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formance (Morgan et al., 2009; Rust et al., 2004). Therefore, we assume that applying AI in customer data analysis positively affects the marketing performance of small and medium-sized enterprises in many ways.

H1a: The application of AI in customer data analysis positively impacts the market performance of SMEs.

H1b: The application of AI in customer data analysis positively impacts the customer performance of SMEs.

H1c: The application of AI in customer data analysis positively impacts the financial performance of SMEs.

H1d: The application of AI in customer data analysis positively impacts the communication performance of SMEs.

Artificial intelligence application enables businesses to personalize marketing activities based on real-time analysis of big data on customer behavior, preferences, and context, thereby enhancing the relevance and effectiveness of marketing activities (Davenport et al., 2020; Huang & Rust, 2021). AI-based personalization helps businesses reach target markets, enhance customer experience, increase satisfaction and loyalty, and use marketing resources more efficiently (Morgan et al., 2009; Rust et al., 2004). Therefore, we assume that applying AI in marketing personalization positively affects marketing performance in many ways.

H2a: The application of AI in personalizing marketing activities positively impacts the market performance of SMEs.

H2b: The application of AI in personalizing marketing activities positively impacts the customer performance of SMEs.

H2c: The application of AI in personalizing marketing activities positively impacts the financial performance of SMEs.

H2d: The application of AI in personalizing marketing activities positively impacts the communication performance of SMEs.

The application of artificial intelligence in marketing automation helps businesses execute marketing processes more quickly, accurately, and consistently, while also enhancing their ability to respond flexibly to market changes (Davenport et al., 2020; Huang & Rust, 2021). Through automation, businesses can improve market access efficiency, enhance customer interaction quality, reduce marketing costs, and optimize resource allocation (Morgan et al., 2009; Rust et al., 2004). Therefore, applying AI in marketing automation is expected to positively affect businesses' marketing performance.

H3a: The application of AI in marketing automation positively impacts the market performance of SMEs.

H3b: The application of AI in marketing automation positively impacts the customer performance of SMEs.

H3c: The application of AI in marketing automation positively impacts the financial performance of SMEs.

H3d: The application of AI in marketing automation positively impacts the communication performance of SMEs.

The application of artificial intelligence in communication and customer interaction allows businesses to maintain continuous, personalized, and real-time communication across multiple channels, thereby improving the quality and effectiveness of marketing communications (Davenport et al., 2020; Huang & Rust, 2021). Effective AI-based interaction helps businesses improve customer experience, increase engagement, loyalty, and conversion from interaction to purchase behavior (Verhoef et al., 2021; Wedel & Kannan, 2016). Therefore, we suggest that the application of AI in communication and customer interaction positively affects marketing performance in various aspects.

H4a: The application of AI in communication and customer interaction positively impacts the market performance of SMEs.

H4b: The application of AI in communication and customer interaction positively impacts the customer performance of SMEs.

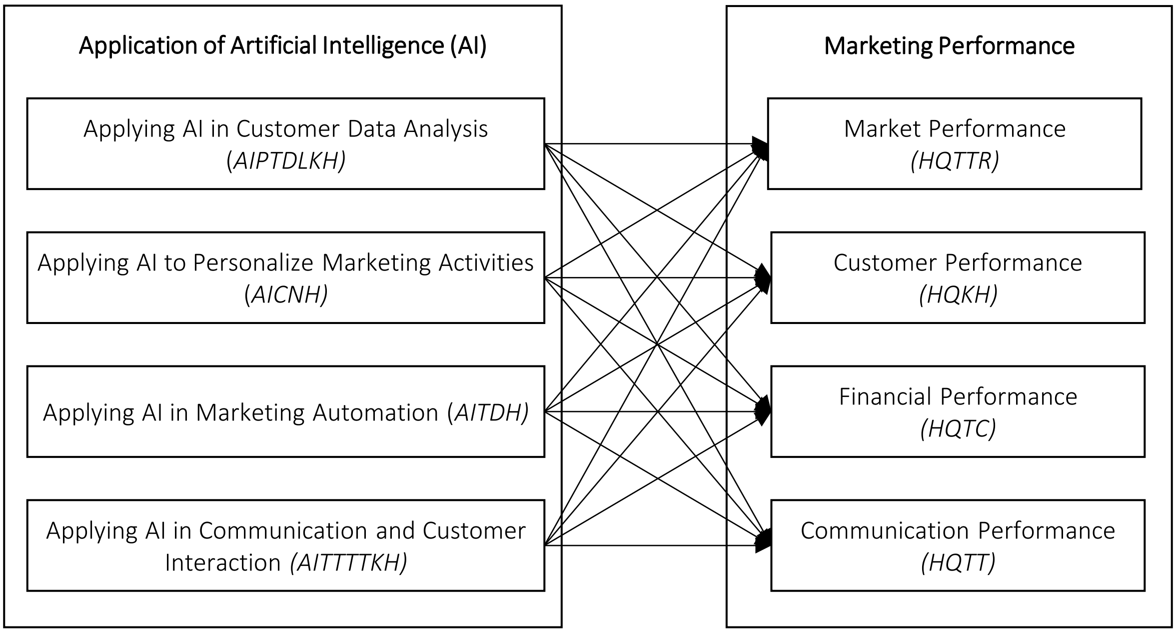

Figure 1. Proposed research model

H4c: *The application of AI in communication and customer interaction positively impacts the financial performance of SMEs.*

H4d: *The application of AI in communication and customer interaction positively impacts the communication performance of SMEs.*

This study aims to empirically examine the effects of AI application on four dimensions of market performance among SMEs in Hanoi, Vietnam. These hypotheses form the conceptual research model presented in Figure 1, in which the four AI application dimensions are specified as antecedents of the four dimensions of marketing performance. The proposed model provides the analytical framework for empirically testing the hypothesized relationships.

2. METHOD

2.1. Research design

This study adopts a quantitative research design to examine the impact of artificial intelligence (AI) application on marketing performance in small and medium-sized enterprises (SMEs) in Hanoi, Vietnam. A cross-sectional survey was conducted among SME managers and employees directly involved in marketing, digital transformation, or AI-related activities to ensure respondents possessed adequate knowledge of AI applications within their organizations. The measurement scales were adapted from established studies and refined through a pilot test before the main survey. In addition to the main constructs, information on firm characteristics, including industry sector, firm size, years of operation, and AI adoption experience, was collected. The data were analyzed using structural equation modeling (SEM) with AMOS, which enables the simultaneous assessment of both measurement and structural models.

2.2. Measurement development

The measurement scales were adapted from established studies and modified to fit the context of AI application in marketing. A five-point Likert scale ranging from 1 (strongly disagree) to 5 (strongly agree) was used to measure all constructs. The constructs include AI application in customer data analytics; AI application in marketing personalization; AI application in marketing automation; AI application in communication and customer interaction; and marketing performance, measured through four dimensions: market, customer, financial, and communication performance. Academic experts reviewed the initial questionnaire to ensure content validity, and we

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subsequently pilot-tested it with a small group of respondents to improve clarity and reliability. A back-translation procedure was applied to ensure linguistic equivalence between the English and Vietnamese versions of the questionnaire. Table A1, Appendix A, shows measurement scales.

2.3. Data collection and sample

Data were collected from SMEs in Hanoi, Vietnam. A combination of purposive and convenience sampling techniques was employed. Respondents were retained only if they confirmed direct involvement in using, supervising, or evaluating AI-enabled marketing tools and had access to information on firm marketing outcomes. Because the dependent variables capture firm-level marketing outcomes, respondent competence was treated as an important eligibility condition. Participants were included only when they had direct experience in using, supervising, or observing AI-enabled marketing applications and sufficient knowledge of marketing activities. Respondents who could not confirm such experience were excluded before data analysis.

A total of 270 questionnaires were distributed through both online and direct survey methods. After eliminating incomplete and inconsistent responses, 237 valid questionnaires were retained for analysis, resulting in a valid response rate of 87.8%. To improve data quality, respondents were informed that participation was voluntary and anonymous. No personal identifiers were collected, and all responses were used exclusively for academic research purposes. Data collection was conducted between January 10, 2026, and February 15, 2026. The demographic information is shown in Table 1.

Table 1. Demographic statistics

Characteristic	Item	Quantity	Percentage (%)
Gender	Male	105	44.3
	Female	132	55.7
Education	High school degree	21	8.9
	College degree	23	9.7
	University degree	95	40.1
	Postgraduate degree	71	30.0
	Other	27	11.4
Income (million Vietnamese dong)	Below 7	28	11.8
	From 7 to 15	97	40.9
	From 15 to 25	50	21.1
	Over 25	62	26.2
Age	Under 25 years old	54	22.8
	25–30 years old	115	48.5
	30–50 years old	49	20.7
	Over 50 years old	19	8.0
Position	Manager	19	8.0
	Vice president	28	11.8
	Staff/Specialist	107	45.1
	Collaborator	54	22.8
	Other	29	12.2
Industry sector	Manufacturing	74	31.2
	Trading	49	20.7
	Services	58	24.5
	Logistics	34	14.3
	Others	22	9.3
Firm size (employees)	< 10	61	25.7
	10–49	104	43.9
	50–199	72	30.4
Years of operation	< 3 years	36	15.2
	3–5 years	58	24.5
	6–10 years	71	30.0
	> 10 years	72	30.4
AI adoption experience	< 1 year	52	21.9
	1–3 years	98	41.4
	> 3 years	87	36.7

2.4. Data analysis technique

Data analysis was conducted using SPSS 26.0 and AMOS 24.0 software. The analysis followed a two-step approach recommended by Hair et al. (2010).

First, confirmatory factor analysis (CFA) was performed to assess the measurement model. The reliability of constructs was evaluated using Cronbach's alpha and composite reliability (CR), while convergent validity was assessed using factor loadings and average variance extracted (AVE). Discriminant validity was examined by comparing the square root of AVE with inter-construct correlations. Second, structural equation modeling (SEM) was used to test the hypothesized relationships between latent variables. Model fit was assessed using multiple indices, including Chi-square/df, Comparative Fit Index (CFI), Goodness-of-Fit Index (GFI), Root Mean Square Error of Approximation (RMSEA), and PCLOSE. Acceptable model fit thresholds were based on established guidelines (e.g., CFI ≥ 0.90, RMSEA ≤ 0.06, Chi-square/df ≤ 3).

2.5. Data availability and ethical considerations

Data were collected from SMEs operating in Hanoi, Vietnam, using a structured questionnaire. The study used convenience and purposive sampling to ensure respondents had relevant experience in marketing or managerial roles within SMEs. The datasets supporting the findings of this study are available from the corresponding author upon reasonable request. We are willing to provide the research data and related materials to ensure transparency and research integrity.

This study followed ethical guidelines for research involving human participants in accordance with COPE standards. Respondents were informed about the purpose of the study and provided informed consent prior to participation. The study collected no personally identifiable information and used all data strictly for academic purposes. The study stored data securely and handled them confidentially throughout the research process.

3. RESULTS

3.1. Reliability measurement assessment

To evaluate the scales, the study used Cronbach's Alpha coefficient (Ca) with Ca > 0.6 and total variable correlation coefficient > 0.3. Variables that did not meet the criteria were considered low-reliability or junk variables and were removed. The dynamically measured Ca values ranged from 0.856 to 0.938 (> 0.6). The results are shown in Table 2.

Table 2. Cronbach's alpha results

Element	Cronbach's alpha (Ca)
Applying AI in customer data analysis	0.867
Applying AI to personalize marketing activities	0.869
Applying AI in marketing automation	0.890
Applying AI in communication and customer interaction	0.897
Market performance	0.891
Customer performance	0.856
Financial performance	0.865
Communication performance	0.938

3.2. Exploratory factor analysis (EFA)

The results of the exploratory factor analysis (EFA) for eight variables are as follows: KMO = 0.928 (0.5 ≤ KMO ≤ 1); Sig Bartlett's Test = 0.000 < 0.05; Eigenvalue = 1.009 > 1. The total variance extracted from these eight factors is 62.838% > 50%, so the eight extracted factors explain 62.838% of the data variation of the 40 observed variables participating in the EFA. This result indicates that the variables are correlated in the population and that factor analysis is appropriate. Table A2, Appendix A, shows the rotated matrix results.

To ensure the unidimensionality of the observed variables, a necessary and sufficient condition is that the measurement model fits the collected research data, except in cases where the errors of the observed variables are correlated with each other (Hair et al., 2010). To determine this fit, this study uses the following indicators: CMIN/df, CFI, GFI, RMSEA, and PCLOSE index (Table 3).

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Table 3. Summary of CFA analysis results

Index	Recommended value	Result	Evaluate
CMIN/df	≤2	1.612	Good
GFI	0.8 < GFI < 0.9	0.817	Acceptable
CFI	≥0.9	0.928	Good
RMSEA	≤0.06	0.051	Good
PCLOSE	≥ 0.05	0.383	Good

3.3. Reliability, convergence, and discriminant validity

To verify reliability, the study evaluated the standardized loading factor and composite reliability. The standardized loading factor must be greater than or equal to 0.5 (ideally greater than or equal to 0.7), and the composite reliability must be greater than or equal to 0.7. Table 4 shows the test results.

To test the convergence of the study, the evaluation was based on the AVE values, with the criterion that the AVE index must be greater than or equal to 0.5. The analysis results showed that all AVE values met the requirement (>= 0.5), thus ensuring convergence.

To achieve discriminability, the MSV indices must be smaller than the corresponding AVE indices. At the same time, the SQRTAVE indices must be larger than the Inter-Construct Correlations indices. Therefore, these results indicate that the criteria for evaluating discriminability are met.

Table 4. Results of CR, AVE, MSV and SQRTAVE assessment

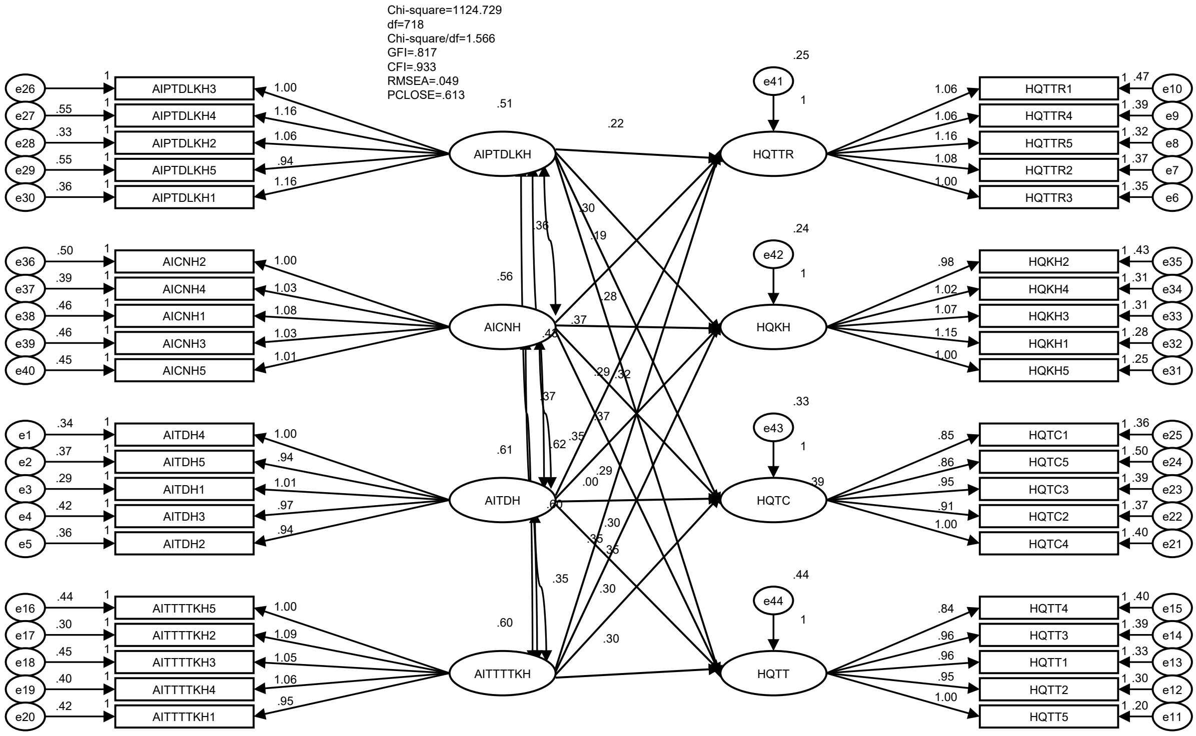
	CR	AVE	MSV	MaxR(H)	AITDH	HQTTR	HQTT	AITT TTKH	HQTC	AIPT DLKH	HQKH	AICNH
AITDH	0.893	0.625	0.358	0.895	0.790							
HQTTR	0.892	0.624	0.373	0.895	0.422***	0.790						
HQTT	0.940	0.760	0.437	0.946	0.311***	0.611***	0.872					
AITTTTKH	0.899	0.640	0.440	0.902	0.387***	0.597***	0.661***	0.800				
HQTC	0.864	0.560	0.427	0.867	0.328***	0.448***	0.584***	0.653***	0.749			
AIPTDLKH	0.873	0.580	0.378	0.879	0.408***	0.451***	0.615***	0.418***	0.405***	0.762		
HQKH	0.860	0.551	0.111	0.863	0.333***	0.210**	0.033	0.067	-0.052	0.317***	0.743	
AICNH	0.859	0.549	0.440	0.862	0.599***	0.586***	0.555***	0.663***	0.603***	0.523***	0.070	0.741

Note: HQTTR means market performance; HQKH means customer performance; HQTC means financial performance; HQTT means communication performance; AIPTDLKH means applying AI in customer data analysis; AICNH means applying AI to personalize marketing activities; AITTTTKH means applying AI in communication and customer interaction.

Table 5. Structural path estimates and hypothesis-testing results

Hypothesis	Structural path			Standardized estimate	SE	CR	P	Evaluate
H1a	HQTTR	←	AIPTDLKH	.219	.077	2.828	.005	Accepted
H1b	HQKH	←	AIPTDLKH	.186	.077	2.422	.015	Accepted
H1c	HQTC	←	AIPTDLKH	.174	.089	1.962	.048	Accept
H1d	HQTT	←	AIPTDLKH	.620	.106	5.873	***	Accept
H2a	HQTTR	←	AICNH	.251	.097	2.587	.010	Accept
H2b	HQKH	←	AICNH	–.390	.102	–3.814	***	Not accepted
H2c	HQTC	←	AICNH	.338	.114	2.966	.003	Accept
H2d	HQTT	←	AICNH	.357	.126	2.837	.005	Accept
H3a	HQTTR	←	AITDH	.229	.074	3.101	.002	Accept
H3b	HQKH	←	AITDH	.273	.075	3.640	***	Accept
H3c	HQTC	←	AITDH	.004	.084	.046	.963	Not accepted
H3d	HQTT	←	AITDH	–.002	.094	–.025	.980	Not accepted
H4a	HQTTR	←	AITTTTKH	.152	.080	1.896	.058	Not accepted
H4b	HQKH	←	AITTTTKH	.295	.083	3.542	***	Accept
H4c	HQTC	←	AITTTTKH	.303	.095	3.187	.001	Accept
H4d	HQTT	←	AITTTTKH	.304	.105	2.902	.004	Accept

Note: HQTTR means market performance; HQKH means customer performance; HQTC means financial performance; HQTT means communication performance; AIPTDLKH means applying AI in customer data analysis; AICNH means applying AI to personalize marketing activities; AITTTTKH means applying AI in communication and customer interaction.



Note: HQTTR means market performance; HQKH means customer performance; HQTC means financial performance; HQTT means communication performance; AIPTDLKH means applying AI in customer data analysis; AICNH means applying AI to personalize marketing activities; AITTTTKH means applying AI in communication and customer interaction.

Figure 2. SEM model analysis

3.4. Structural model analysis (SEM)

The validation results (Figure 2) show that all relevant analytical indicators meet the necessary standards, confirming that the research model is appropriate for the collected research data. Specifically: Chi-square/df reached a value of 1.566, less than 2; GFI reached 0.817; CFI reached 0.933; Thus, the CFI index is greater than 0.9, and 0.8 < GFI < 0.9. At the same time, the RMSEA index was 0.049 (less than 0.06), and PCLOSE was 0.613 (greater than 0.05), according to the standards of Hair et al. (2010).

Finally, in Table 5, we have the independent variables that are statistically significant, impacting 53.9%, 30.2%, 47.9%, and 60.6% of the data variation for the variables HQTTR, HQKH, HQTC, and HQTT, respectively.

4. DISCUSSION

The empirical results provide evidence that artificial intelligence (AI) application play a significant role in enhancing marketing performance in small and medium-sized enterprises (SMEs) in Hanoi, Vietnam. However, the magnitude and direction of these effects vary across different AI dimensions and marketing performance outcomes.

First, AI-based customer data analytics has a consistently positive impact on all dimensions of marketing performance, with the strongest effect on communication performance. This result aligns with Davenport et al. (2020) and Huang and Rust (2021), who emphasize the central role of data-driven decision-making in improving marketing effectiveness. The result suggests that SMEs benefit most from AI when it is used to interpret customer data and support real-time marketing decisions.

Second, AI-driven marketing personalization shows mixed effects. While it positively influences market, financial, and communication performance, it has a negative and statistically significant effect on customer performance. The negative coefficient for the relationship between AI-enabled marketing personalization and customer performance is unexpected. This result should be

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interpreted cautiously. The bivariate association between the two constructs is weak, whereas the coefficient becomes negative after the other AI dimensions are simultaneously included in the structural model. This pattern may indicate a suppression or model-specification effect rather than a straightforward adverse effect of personalization. Additional diagnostic analyses are therefore needed before advancing a substantive causal explanation.

This finding is inconsistent with prior studies (Verhoef et al., 2021), which generally report positive effects of personalization. One possible substantive interpretation is that personalization may not automatically improve customer outcomes when implementation quality, data accuracy, transparency, or customer acceptance is insufficient. Prior research has generally emphasized the benefits of relevant and timely personalization. However, other streams of research suggest that highly targeted communication may generate discomfort when consumers perceive it as intrusive or difficult to control. Because privacy perceptions, trust, personalization quality, and communication fatigue were not measured in the present study, these explanations remain theoretical possibilities rather than empirically verified mechanisms. Accordingly, the present finding should be regarded as an unexpected association that requires replication using alternative samples, additional control variables, and direct measures of consumer responses to AI-enabled personalization.

Third, AI-based marketing automation positively affects market and customer performance but does not show significant effects on financial and communication performance. This suggests that SMEs in Hanoi are still in the early stages of automation adoption, where operational efficiency gains have not yet fully translated into financial outcomes. This result is consistent with the argument of Rust (2020), who emphasizes that the benefits of AI adoption often require time and organizational maturity to materialize.

Fourth, AI-enabled communication and customer interaction significantly improve customer, financial, and communication performance, but have no significant effect on market performance. This finding supports Wedel and Kannan (2016), who found that customer interaction technologies primarily enhance engagement and experience rather than directly influencing market expansion.

Overall, the findings confirm that communication performance and customer-related outcomes are the most strongly influenced dimensions of AI applications in SMEs. This highlights the importance of customer-facing AI technologies in resource-constrained firms operating in emerging markets. From a theoretical perspective, this study extends the resource-based view (RBV) and dynamic capabilities theory (DCT) by demonstrating that AI should be conceptualized as a multidimensional capability rather than a single construct. The results also show that different AI capabilities generate heterogeneous effects on marketing performance dimensions. From a practical perspective, the findings suggest that SMEs should prioritize AI investments in customer data analytics and communication technologies, while carefully managing the implementation of personalization strategies to avoid negative customer reactions.

CONCLUSION

This study aimed to examine the impact of artificial intelligence (AI) application on marketing performance in SMEs in Hanoi, Vietnam. The findings show that AI-enabled marketing personalization was positively associated with market, financial, and communication performance. However, the hypothesized positive relationship between personalization and customer performance was rejected because the estimated coefficient was negative and statistically significant. This unexpected result should not be interpreted as conclusive evidence that personalization reduces customer performance, as supplementary tests are required to exclude possible multicollinearity, suppression, measurement overlap, or sample-composition effects.

These findings offer theoretical contributions by extending the application of resource-based view (RBV) and dynamic capabilities theory (DCT) in explaining AI-driven marketing performance in SMEs operating within an emerging economy. The study also contributes to the AI marketing literature by examining AI as a multidimensional construct rather than a single technological capability. From a managerial perspective, SME managers should prioritize investments in customer data analytics and AI-supported communication systems, as these dimensions generate the most consistent performance benefits. In addition, organizations should carefully design AI personalization strategies to avoid excessive automation that may negatively influence customer perceptions. Policymakers may also support SME digital transformation through training programs, technological infrastructure development, and AI adoption incentives.

Despite these contributions, the study is limited by its cross-sectional design, focus on SMEs located in Hanoi, and reliance on self-reported data. Future research may employ longitudinal data, comparative regional studies, and mediating or moderating variables to further investigate the mechanisms through which AI applications affect organizational performance.

AUTHOR CONTRIBUTIONS

Conceptualization: Hung Do Hai.
Data curation: Hung Do Hai, Tuan Anh Le.
Formal analysis: Hung Do Hai.
Investigation: Hung Do Hai, Tuan Anh Le.
Methodology: Hung Do Hai.
Project administration: Hung Do Hai.
Resources: Hung Do Hai.
Software: Hung Do Hai, Tuan Anh Le.
Supervision: Hung Do Hai.
Validation: Hung Do Hai.
Visualization: Hung Do Hai.
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Writing – review & editing: Hung Do Hai.

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APPENDIX A

Table A1. Measurement scales

Variable	Content	Source
Applying AI in customer data analysis		Davenport et al. (2020), Wedel and Kannan (2016), Kumar et al. (2016)
AIPTDLKH1	Businesses use AI to analyze customer behavior data	
AIPTDLKH2	AI helps businesses better understand customer needs and preferences	
AIPTDLKH3	Businesses use AI to forecast customer trends and needs	
AIPTDLKH4	AI supports more accurate customer segmentation	
AIPTDLKH5	The results of AI data analysis are used in marketing decisions	
Applying AI in personalized marketing activities		Huang and Rust (2021), Davenport et al. (2020), Verhoef et al. (2009)
AICNH1	Businesses use AI to personalize marketing content for customers	
AICNH2	AI helps recommend products or services tailored to each customer	
AICNH3	Marketing messages are tailored to each customer group thanks to AI	
AICNH4	AI helps improve the personalized marketing experience for customers	
AICNH5	Business marketing activities are effectively personalized thanks to AI	
Applying AI in marketing automation		Davenport et al. (2020), Morgan et al. (2009)
AITDH1	Businesses are using AI to automate repetitive marketing activities	
AITDH2	AI helps deploy marketing campaigns faster and more efficiently	
AITDH3	AI supports automated customer journey management.	
AITDH4	The application of AI reduces the workload of manual marketing tasks	
AITDH5	AI-powered marketing automation improves marketing efficiency	
Applying AI in communication and customer interaction		Huang and Rust (2021), Verhoef et al. (2009)
AITTTTKH1	Businesses use chatbots or virtual assistants to interact with customers	
AITTTTKH2	AI helps businesses respond to customers quickly and promptly	
AITTTTKH3	AI supports interaction with customers across multiple communication channels	
AITTTTKH4	AI helps improve the quality of communication between businesses and customers	
AITTTTKH5	The application of AI enhances the effectiveness of customer interaction	
Market performance		Morgan et al. (2009), Rust et al. (2004)
HQTTR1	The business has attracted more new customers	
HQTTR2	The business's market share has increased	
HQTTR3	The business's ability to reach its target market has improved	
HQTTR4	The business's competitive position in the market has increased	
HQTTR5	The business is expanding its market more effectively than before	
Customer performance		Rust et al. (2004), Verhoef et al. (2009)
HQKH1	Customer satisfaction with the business improves	
HQKH2	Customers tend to stay loyal to the business for the long term	
HQKH3	Customer loyalty to the brand increases	
HQKH4	The rate of repeat customers improves	
HQKH5	The relationship between the business and the customer becomes stronger	
Financial performance		Morgan et al. (2009), Rust et al. (2004)
HQTC1	Revenue from marketing activities of businesses increased	
HQTC2	Marketing costs are used more effectively	
HQTC3	Profits from marketing activities are improved	
HQTC4	Conversion rates from marketing to sales increase	
HQTC5	Overall financial efficiency from marketing is enhanced	
Communication performance		Davenport et al. (2020), Wedel and Kannan (2016)
HQTT1	Customer engagement with media content increases	
HQTT2	Marketing messages are conveyed more effectively	
HQTT3	Brand image in customer perception improves	
HQTT4	Marketing communication channels operate more effectively	
HQTT5	Marketing communication activities achieve their set goals	

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Table A2. EFA analysis results

Pattern Matrix								
	Factor							
	1	2	3	4	5	6	7	8
HQTT5	.959							
HQTT2	.916							
HQTT1	.758							
HQTT3	.744							
HQTT4	.726							
AITDH1		.925						
AITDH4		.786						
AITDH3		.759						
AITDH5		.710						
AITDH2		.708						
HQTC4			.839					
HQTC2			.794					
HQTC3			.698					
HQTC5			.629					
HQTC1			.611					
HQTTR3				.835				
HQTTR2				.821				
HQTTR5				.774				
HQTTR4				.700				
HQTTR1				.589				
AIPTDLKH3					.875			
AIPTDLKH4					.771			
AIPTDLKH2					.739			
AIPTDLKH1					.714			
AIPTDLKH5					.588			
HQKH5						.811		
HQKH3						.733		
HQKH4						.730		
HQKH2						.698		
HQKH1						.686		
AITTTTKH3							.778	
AITTTTKH2							.742	
AITTTTKH4							.733	
AITTTTKH5							.712	
AITTTTKH1							.707	
AICNH4								.812
AICNH5								.755
AICNH3								.728
AICNH2								.704
AICNH1								.526

Note: HQTTR means market performance; HQKH means customer performance; HQTC means financial performance; HQTT means communication performance; AIPTDLKH means applying AI in customer data analysis; AICNH means applying AI to personalize marketing activities; AITTTTKH means applying AI in communication and customer interaction.

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