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The Impact of Generative AI on Marketing Efficiency: Reducing Costs and Improving Economic Performance of SMEs

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Abstract **Original Research Article**

This study explores how the emergence of Generative Artificial Intelligence (GenAI) offers many new choices for small and medium-sized enterprises (SMEs) to improve marketing effectiveness and improve economic performance. However, most of the current research focuses on big companies, which still limits the understanding of how GenAI impacts marketing activities in SMEs with limited resources. Therefore, this study aims to identify a conceptual model, examine the impact of artificial intelligence on marketing effectiveness and their other factors on economic performance in the SME marketing market. In line with the theory of technology adoption and organizational capabilities, this study identifies the technological factors of GenAI including automation of personnel, data analysis and data-driven decision making, changing the perspective and showing their impacts on employee productivity and internal marketing. This research method is applied by combining, firstly, Delphi study to correct the model in the right direction and then quantitative survey to evaluate the relationships in the structures. Our research will provide empirical evidence that GAI helps to reduce budget, time and optimize greatly in human resources and better decision-making orientation, thereby improving marketing efficiency and contributing greatly to the economic efficiency of SMEs. The results of this research will contribute greatly when managers at the top of SMEs in applying AI to create accurate and effective marketing activities.

Keywords: Generative Artificial Intelligence, Marketing Effectiveness, Small and Medium-sized Enterprises, Economic Performance, Technology Adoption.

1. Introduction

The rapid expansion of GAI has changed the way SMEs manage and improve their marketing performance, while also reducing costs to improve their bottom line. According to the Organization for Economic Cooperation and Development (OECD), more than 43% of SMEs worldwide have used at least one GAI-based marketing application, up from 37% in 2023 (OECD, 2024). This has boosted GAI in automating creative processes, creating promotional content and optimizing decision-making with resources. Unlike traditional artificial intelligence that mainly analyzes predictions, GenAI has the ability to create new content, allowing employees to produce marketing products with up about 40-60% higher efficiency and 25% to 40% lower costs across larges company (McKinsey, 2024). Although these estimates are given from general business data, SMEs are also expected to have similar breakthrough expectations, albeit at a slightly lower level due to limited resources.Therefore, this transformation has reshaped the position and role of the marketing department, requiring employees to adapt to a collaborative model between humans and AI, thereby directly impacting marketing productivity and cost management at SMEs.

For SMEs, budget and human resources are limited, so GenAI brings both opportunities and challenges for them. When these technologies help employees automate repetitive tasks, increase the accuracy of strategies as well as improve marketing efficiency (PwC, 2024). Some reports indicate that applying GenAI in marketing allows SMEs to speed up content production and improve message consistency in campaigns while reducing operating costs (Deloitte, 2025). On the other hand, many SMEs are struggling to integrate technologies together to create the best efficiency but due to low digital literacy or uncertainty about profits (Kallmuenzer, Mikhaylov, Chelaru, & Czakon, 2025). In Vietnam, although about 60% of SMEs are interested in applying AI tools, only about 28% deploy them most effectively in marketing due to cost and training barriers.

Previous studies have focused only on AI applications in large corporations or on customer behavior analysis (Hossan, 2024), leaving a gap in studies that consider GAI from an employee- and SME-centric perspective. Although the technological power of GAI has been recognized, empirical evidence on how GAI improves marketing effectiveness and economic outcomes for SMEs remains scarce, especially in developing economies such as Vietnam (Jahanbakhsh, 2025). Addressing this research gap is necessary to guide SMEs in exploiting GAI to improve marketing effectiveness.

Therefore, this study aims to explore the impact of Gen AI adoption on marketing effectiveness and economic performance of SMEs in Vietnam. By focusing on employee adaptability, organizational capacity and technology utilization, it will provide further insights into how SMEs can effectively deploy Gen AI to optimize processes, reduce operating costs and improve marketing effectiveness for better economic results.

2. Literature review and Hypotheses development

2.1. Previous studies

2.1.1. Generative Artificial Intelligence in Marketing

GenAI is a deep learning model that focuses on developing synthetic data, text, images, videos, and 3D models. Therefore, GenAI has revolutionized marketing activities, such as writing articles, strategic orientation, and future market research (Estevez, Ballestar, & Sainz, 2025). Unlike large corporations, SMEs often do not have enough resources for large-scale marketing or a strong team of employees, GenAI brings autonomy to marketing capacity. A recent study on SMEs in London suggests that using AI helps to automatically write marketing content, personalize more effectively in digital marketing activities, thereby reducing costs for businesses (Nyantakyi & Farooq, 2024).

2.1.2. Generative AI and Perceived Credibility in Digital Marketing

Perceived credibility comes from the measure of trust, sincerity, and professionalism of the marketing message that a business communicates to the media. High credibility contributes to customer trust, while also contributing to increased business performance (Nguyen, 2022). GenAI creates marketing credibility with high-quality advertising, consistent with brand recognition, making anyone who sees the next project know whose brand it is. In addition, AI-generated documents increase SMEs' recognition in the market due to professionalism (Lee, 2024).

2.1.3. Generative AI and Marketing Efficiency in SMEs

Marketing efficiency is the result of marketing activities with time, cost, and human resources. For SMEs, improving marketing efficiency needs to be strongly developed because they have limitations.

Some studies found that GenAI automates the updating of duplicate steps, especially marketing automation for SMEs in automatically scheduling social media posts, helping to speed up marketing by more than 60% compared to traditional methods.

Furthermore, GenAI improves targeting, allowing businesses to analyze product and service data, improving project accuracy (School, 2025). It has been proven that many companies that have used GenAI report higher marketing ROI and reduced the likelihood of creative ideas being lost. For example, global technology company Klarna saved more than $10 million per year in marketing cash flow after using GenAI tools (Mukherjee, 2024).

2.1.4. Marketing Efficiency, Credibility, and Economic Performance of SMEs

Previous studies has highlight a relationship between marketing efficiency, credibility, and SME performance, suggesting that improved credibility and cost efficiency may contribute to stronger economic outcome. The issue of cost reduction and profit improvement shows a high marketing performance scale because SMEs reach the market with a large scale. From 30-50% of campaign operating costs are cut without affecting the quality of marketing interactions (Butterfield, 2025). At the same time, customer trust in the company's brand also stabilizes a significant source of revenue. The focus for this research is marketing efficiency and credibility promoted in parallel to bring high economic performance, improving the competitiveness of the marketing market (Acxiom, 2024).

However, most of the research to date has mainly explored Gen AI in marketing from the customer perspective for large corporations or industries in general, while few studies have explored how AI contributes to marketing effectiveness and reputation in SMEs. In addition, the scales of performance and capabilities related to Gen AI vary across studies, leading to conceptual inconsistencies. Therefore, this research first conducted a Delphi study to confirm the key factors involved before further developing the research hypotheses.

2.2. Theoretical foundation

2.2.1. Generative AI in marketing: a paradigm shift for SMEs

In recent years, the strong development of Generative AI (GenAI) has created a major turning point in marketing activities, especially at the small and medium enterprise (SMEs) level. Not only a data analysis tool, GenAI also has the ability to automatically create marketing content, advertising ideas, so it helps companies save time, cut expenses and increasing productivity in marketing operations (Dwivedi, 2024). Recent studies show that Generative AI supports businesses in three main groups of marketing activities:

Firstly, automation and optimization of marketing processes allow many companies to significantly reduce time for repetitive activities such as writing content, creating images, and planning campaigns (Rahman & Alam, 2023). This helps employees focus more on innovation and strategy to deliver better value. Secondly, Predictive analytics allows companies' marketing teams to analyze big data sources, predict market trends, and make more informed operational decisions regarding pricing or promotion timing (Li & Singh, 2024). Thirdly, AI also supports decision making and knowledge generation, which significantly enhances employees' ability to plan, evaluate, and adjust marketing strategies more effectively, leading to huge improvements in organizational performance.

By intergrating these capabilities, businesses applying GenAI also recorded a significant increase in economic performance thanks to reduced marketing costs, optimized human resources and increased revenue through targeted advertising (Gao & Liu, 2023). However, most of these studies only focus on the general level or in large corporations, without a specific theoretical framework to measure the impact of Generative AI on SMEs - where resources are limited, the ability to invest in technology is low, but they are under greater competitive pressure. Therefore, it is necessary to build a separate research model for SMEs to clarify the relationship between technology - marketing efficiency - economic efficiency.

2.2.2. Concept and role of technology factors in SMEs

In the current competitive environment, technological capability is considered a strategic resource that helps SMEs achieve sustainable competitive advantage (Barney, 1991; Teece, 2018). For Generative AI, technology factors can be divided into eight main capabilities, reflecting the extent to which businesses apply and exploit AI in marketing activities:

Firstly, AI-enabled Personalization (AIP) refers to the ability to use AI to personalize content and marketing messages for each customer group, to increase engagement and loyalty. Secondly, Content Creation Efficiency (CCE) highlights the capacity of AI to automate the content creation process (images, articles, videos) to save time and production costs. Thirdly, Predictive Analytics (PRA) emphasizes the ability of AI to predict market trends, consumer behavior and campaign effectiveness, thereby helping businesses make more accurate decisions. Fourthly, Data-driven Decision Making (DDD) represents the extent to which businesses rely on AI-powered data analysis to plan marketing strategies. Fifthly, Automation Level (AUT) demonstrates how marketing activities such as customer management, email sending, customer care, feedback analysis, etc. Sixthly, Innovation Capability (INC) reflects the firm's ability to integrate AI creatively in developing new strategies or products that strengthen competitive advantages. Seventhly, Brand Visibility & Awareness (BVA) focus on how businesses employ AI to enhance brand recognition, expand online influence, and increase customer reach. Finally, Market Segmentation (MKS) shows how effectively companies use AI to analyze customer data and identify target groups more precisely.

These factors form the core set of technological capabilities of businesses when deploying Generative AI, playing the role of input for improving marketing effectiveness (MAE) and economic efficiency (ECP).

2.2.3.Integrating Technology-Organization-Environment (TOE) and Dynamic Capabilities (DCs)

The integration of the TOE model (Tornatzky & Fleischer, 1990) and DCs theory provides a theoretical basis for explaining the way SMEs use Gen AI effectively. The TOE framework highlight that technology adoption depends on three contextual factors. First of all, many technological factors such ass the perceived usefulness and compatibility of AI tools. Then, organizational factors including company size, management support, and digital readiness. Next, environmental factors such as competitive pressures and market dynamics (Oliveira & Martins, 2011).

However, TOE simply explains why businesses purchase technology, not how they learn and adapt using the technology. Therefore, DCs integration fills the gap by focusing on the SME's ability to recognize, acquire, and reorganize resources to take advantage of AI-generated opportunities (Teece, 2018). This integration provides a holistic view of AI adoption, from choosing to deploy the technology to continuously improving marketing performance through learning and adaptation.

2.2.4. TCP (Technology–Capability–Performance) theoretical model

To explain the relationship between technology adoption and business performance, this study employs the TCP theoretical framework, which has been widely applied in digital transformation research (Teece, 2018; Dwivedi et al., 2023). Within this framework, Technology represents the level of enterprise investment in and application of technological innovations specifically GenAl as a source of competitive advantage. Capability refers to the firm's ability to organize, integrate, and leverage these technologies to generate tangible business value, which in this study is operationalized as Marketing Efficiency (MAE). Performance, in turn, denotes the measurable outcomes achieved in terms of financial results, productivity, or market share, represented here by Economic Performance (ECP).

According to the TCP framework, technology alone does not directly enhance business outcomes; rather, its effectiveness depends on the firm's ability to transform technological investments into internal operational capabilities. Consequently, MAE serves as a critical mediating factor that converts the influence of technological drivers into concrete economic results, such as cost reduction and profit enhancement.

2.2.5. Proposed Theoretical Framework for the Study

Based on the theoretical overview and research gaps, this paper proposes an integrated theoretical framework to model the relationship between eight technological factors of Generative AI, MAE and ECP in SMEs.

This theoretical framework suggests that technological factors (AIP, CCE, PRA, DDD, AUT, INC, BVA, MKS) will have a positive impact on marketing effectiveness (MAE). When marketing effectiveness is improved, businesses are able to reduce operating costs, improve financial performance and competitiveness (ECP). In addition, some factors such as AIP, PRA and CCE can indirectly impact ECP through MAE. This research model not only contributes to extending the traditional TCP framework to the Generative AI context, but also helps SMEs understand the mechanism of "transforming technology into efficiency" in the digital marketing environment.

2.3. Study 1 – Delphi study

2.3.1. Purpose of the Delphi Study

Since the application of Generative AI in SMEs is a relatively new field, the core technological factors that affect marketing effectiveness have not yet been unified in academia. Therefore, this study uses the Delphi method to reach a consensus among experts on: Technological factors of Generative AI that have a significant impact on MAE. The importance level of each factor in the conceptual model. The results from the Delphi Study will be used to validate and refine the independent variables in the model, before conducting quantitative research or testing hypotheses.

2.3.2. Reasons for choosing the Delphi method

The Delphi method is a structured, iterative process used to collect and unify the opinions of experts in complex fields, when empirical data is limited (Hsu & Sandford, 2007). This method is particularly suitable for research on emerging technologies, such as Generative AI because it allows identifying important factors based on expert knowledge instead of secondary data, maintains the anonymity of participants, eliminating the influence of the leader or dominant opinion. Moreover, it is suitable for adjusting, adding, or removing research variables through feedback loops. In this study, the Delphi method was chosen to ensure that the variables in the research model are both academically valuable and relevant to the practice of SMEs in Vietnam.

2.3.3. Criteria for selecting experts

Experts are selected based on three main criteria. To begin with, professional knowledge: Have in-depth understanding of digital marketing, artificial intelligence, or SMEs management. Next, practical experience have at least 3 years of experience in using or consulting on the implementation of AI technology in business operations. After that, willingness to participate was ensured through voluntary participation and commitment to provide feedback through three Delphi rounds within the specified time. This study have a total of 12 experts participated in the study, including 5 university lecturers specializing in marketing and technology management, 4 managers/entrepreneurs running SMEs in the e-commerce sector, 3 technology consultants in Vietnam, Singapore and Malaysia.

2.3.4. Three-round Delphi Process

Given the early adoption of generative AI in SMEs, empirical frameworks for understanding how this technology enhances marketing effectiveness and economic outcomes are still limited. Therefore, this study used the Delphi method as an exploratory step to explore and validate the important factors influencing the link between generative AI, marketing effectiveness, and economic success. Since Generative AI is a relatively new field for SMEs, identifying key technological factors that impact marketing effectiveness should be based on the expert opinions of industry experts. Therefore, this study uses the three-round Delphi method, a systematic and iterative process, to reach a consensus among experts on the most important technological factors of Generative AI for marketing activities in SMEs.

In the first round, 12 experts were asked to list and describe the technological factors of Generative AI that they believe have a important impact on MAE. The results from the responses showed that 11 potential technology factors were proposed, including: AI-enabled Personalization (AIP), Content Creation Efficiency (CCE), Predictive Analytics (PRA), Data-driven Decision Making (DDD), Automation Level (AUT), Innovation Capability (INC), Brand Visibility and Awareness (BVA), Market Segmentation (MKS), Data Security (DSC), Customer Interaction (CIN), and Ethical AI Usage (EAU). After eliminating duplicates, the research team built a list of these 11 factors to be included in the next round of evaluation.

In round two, experts were asked to rate the importance of each factor to MAE on a 7-point Likert scale (1 = not important, 7 = extremely important). The statistical results of round 2 showed that most factors had an average score above 5.0, indicating a relatively high level of relevance. However, some factors such as Data Security (DSC) and Ethical AI Usage (EAU) were rated lower because they do not directly affect marketing activities. Based on the initial criteria (Mean $\geq$ 5.5), only 8 factors were retained for round 3, including: AIP, CCE, PRA, DDD, AUT, INC, BVA, and MKS.

In the final round, the expert group was sent back a summary of the mean and standard deviation results from round 2, and then asked to re-evaluate each factor to determine the final level of importance. The goal of this round was to achieve a consensus of at least 70%, meaning that more than 70% of the experts agreed that the factor had a score $\geq$ 5.5. The results of round 3 showed that the consensus focused on the three most prominent technology factors that have a strong impact on MAE and ECP in SMEs including AIP, CCE, PRA.

The remaining factors, although of academic value, had a lower level of influence and did not reach the 70% consensus threshold, so they were excluded from the research model.

Table 1. Selected to variables potential constructs

Variables	**Academic Definition**	**References**
AI-enabled Personalization (AIP)	The extent to which AI can personalize messages and customer experiences across marketing platforms, enhancing engagement and communication effectiveness.	Gao & Liu (2022); Kim et al. (2024)
Content Creation Efficiency (CCE)	The ability of AI to automate and accelerate content production while maintaining creativity and quality, reducing time and cost.	Rahman & Alam (2023); Levi Strauss & Co. (2023)
Predictive Analytics (PRA)	The use of AI-driven data analysis to predict market trends, customer behaviors, and marketing outcomes for more accurate decision-making.	Li & Singh (2024); Ratajczak (2013)

Data-driven Decision Making (DDD)	The extent to which businesses use AI-processed data to support marketing decisions such as budget allocation, media channel selection and target customer identification, to optimize operational efficiency.	(Gao & Liu, 2023; Kim et al., 2023)
Automation Level (AUT)	The extent to which businesses apply Generative AI to automate marketing processes such as content creation, customer care, and campaign analysis; helping to save costs, reduce errors, and improve marketing efficiency.	(Dwivedi, 2024; Rahman & Alam, 2023)
Market Segmentation (MKS)	The application of AI to divide customers into segments based on data and behaviors, helping firms optimize campaigns and costs.	Ratajczak (2013)
Innovation Capability (INC)	The firm's capability to generate new ideas and creative marketing solutions through AI, enhancing competitiveness.	Sujata Joshi (2024)
Brand Visibility and Awareness (BVA)	The extent to which AI tools increase brand exposure, memorability, and recognition in consumers' minds.	Audrezet (2020)

(Source(s): Author's own work)

2.3.5. Delphi results and Interpretation

The table below shows the mean and standard deviation of the eight technology factors after round 3.

Table 2: Results of round 1 of a Delphi study

Variables	Mean	Standard deviation	Agreement for Importance (rated higher than 5)
AI-enabled Personalization	6.7	0.4	92%
Content Creation Efficiency	6.6	0.5	89%
Automation Level	6.5	0.6	65%
Predictive Analytics	6.5	0.4	87%
Data-driven Decision Making	5.9	0.7	61%
Innovation Capability	5.8	0.6	58%
Brand Visibility & Awareness	5.7	0.5	56%

Market Segmentation	5.6	0.8	54%

(Source(s): Author's own work)

Based on Table 2, AIP scored the highest (Mean = 6.7), which experts considered a key factor in modern marketing. CCE ranked second (Mean = 6.6), demonstrating the importance of AI's ability to automatically generate creative content at low cost and high speed which a factor that is especially important for SMEs with limited resources. PRA ranked third (Mean = 6.5), reflecting the ability to optimize marketing processes, helping to save operating costs and improve productivity. Other factors such as PRA, DDD, INC, BVA and MKS, although theoretically significant, have a low level of consensus, indicating that they are not yet a top priority in the context of GenAI application by SMEs in Vietnam.

2.4. Hypotheses development

This study, based on the TCP model, the TOE framework (Salah & Ayyash, 2024), and DCs (Nasution, Rafiki, Lubis, & Rossanty, 2021) examines how generative AI technologies change marketing operation in the SMEs.

By this integrated perspective, TOE provides technological elements to support, namely AIP, CCE, and PRA that represents the technology platform to support innovative marketing commerce innovation. Additionally, DCs emphasizes that how many companies use these technologies to enhance marketing related capabilities such as PEC and MAE. In particular, this helps companies in improve marketing methods to become more adaptable. Altogether, it highlight that these factors contribute to more business revenue, especially improving economic performance (ECP) in SMEs.

One of the most unique characteristics of generative AI in marketing is its ability to create highly individualized experiences for SMEs. In order to compete with big corporations with strong financial resources in a highly digital environment, this causes SMEs to limit their marketing efforts due to lack of economic advantages (Obinna & Kess-Momoh, 2024). That is why SMEs need to use AI to analyze market trends to create effective marketing strategies. Applying this technology is not only about solving the marketing process but also about SMEs' belief in the effectiveness that AI tools bring.

AI-enabled personalization significantly supports the improvement of marketing plan and analyze data even when SMEs are limited in resources. In particular, SMEs start to believe in the potential of AI tools to effectively support them in their marketing activities, which are considered perceived usefulness (PU) and perceived ease of use (PEOU). These are considered the trust antecedents of PEC, specifically SMEs see AI as a factor to improve their competitiveness with other businesses. (Gabelaia, 2024). For example, 59% of SMEs say AI has improved their business and 45% say it has increased productivity and efficiency. (Schönberger, 2023). Accordingly:

H1a: AI-enabled personalization (AIP) positively influences perceived credibility (PEC).

Besides, AIP improves the efficiency of marketing processes by optimizing and automating processes within a company, which allowmarketing staff to focus on other strategic advertising activities instead of manual work (Obinna & Kess-Momoh, 2024). AI has helped SMEs automatically manage posting, schedule campaigns, and at the same time provide timely analysis to quickly adjust campaign activities and minimize errors (Dinh, Vu, & Tran, 2025). Therefore, SMEs can do more projects at the same cost, increase overall productivity and optimize resource allocation (Olawore, Aiki, Banjo, Okoh, & Olafimihan, 2025). In addition, machine learning also partly supports marketing campaigns on a global scale, ensuring effective policies to minimize resource waste (Kedi, Ejimuda, Idemudia, & Ijomah, 2024). All these factors have proven that AIP has greatly contributed to MAE in SMEs. Therefore, we propose:

H1b: AI-enabled personalization (AIP) positively improves marketing efficiency (MAE).

CCE is quite an important factor for SMEs. Specifically, AI has the ability to produce and manage marketing content effectively by updating creative content such as graphic design from images to videos, creating text or scheduling posts even with limited financial resources (Kumar, Ashraf, & Nadeem, 2024). This has helped SMEs save time and overcome limitations in professional skills. From there, they can create high-quality, beautiful content to launch on the market at the right time. In addition, creating content along with messages for each post must be of high quality, avoiding overlapping meanings with other businesses' marketing, contributing to creating a more stable and professional brand image for the market (A, Bature, I, & Isyaka, 2025). Thus:

H2a: Content creation efficiency (CCE) positively influences perceived credibility (PEC).

AI has helped CCE reduce workload, which allows for instant marketing content creation, increased productivity, and faster response to rapidly changing market demands. Furthermore, CCE allows SMEs to optimize resource allocation by reducing labor costs, production time, and creative costs for each marketing campaign deployed, thereby leading to increased marketing budget efficiency (Wahid, Mero, & Ritala, 2023). This shows that SMEs' ability to adapt to AI in marketing activities is strong, increasing their competitiveness with large enterprises. Accordingly, the study proposed that:

H2b: Content creation efficiency (CCE) significantly enhances marketing efficiency (MAE).

PRA plays a key role in strengthening internal trust in SMEs. PRA has provided valuable data and AI-based predictive models to judge potential risks in management policy decisions, allowing employees and managers to rely on this clear source of information (Madanchian, 2024). Specifically, ensuring that this marketing idea has a solid origin, thereby increasing SMEs' trust in the technology (Pham, Tran, Phung, & Venkatesh, 2017). Furthermore, integrating predictive analytics also helps reduce risks, detect anomalies based on data and increase the performance of continuous marketing strategies (Islam, et al., 2024). SMEs increase their PEC in predictive analytics systems in decision making, accurately guiding their internal company on the right development path (Abdul-Yekeen, Kolawole, Iyanda, & Abdul-Yekeen, 2024). Therefore, we propose:

H3a: Predictive analytics (PRA) positively influences perceived credibility (PEC).

For SMEs, PRA not only improves PEC but also MAE by instantly updating multiple predictive models in visual marketing planning, data, and adjusting the ability to respond in time (Ogeawuchi & Onifade, 2022). This helps SMEs to timely predict projects according to the current market speed (Chatzigeorgiou, Christou, & Simeli, 2025). In addition, (PRA) can provide the most profitable sources, helping SMEs reduce the workforce, implementation process and unnecessary marketing expenditure (Islam, et al., 2024). Thus, our project shows the importance of PRA in shortening the implementation time, reducing costs and increasing marketing performance. Accordingly, the study proposed that:

H3b: Predictive analytics (PRA) positively improves marketing efficiency (MAE).

PEC is the trust that SMEs build in the marketing market, especially social media and digital marketing channels, giving companies a huge competitive advantage. When SMEs have a high perceived credibility, they can build a strong brand presence, offer higher prices and gain a position in the hearts of customers, thereby increasing their economic performance (ECP). A high reputation also reduces costs and risks when negotiating with suppliers, advertising platform investors, and other social media (Magableh, Mahrouq, Ta'Amnha, & Riyadh, 2024). In addition, perceived credibility strengthens customer loyalty relationships, other partners ensuring a stable cash flow for SMEs over the long term. As well as increasing their traffic and interaction with marketing communication campaigns from a trusted brand (Qalati, Ostic, Sulaiman, Gopang, & Khan, 2022). Accordingly, the study proposed that:

H4: Perceived credibility (PEC) positively contributes to the economic performance (ECP) of SMEs.

MAE evaluates the effectiveness of marketing activities when using AI to advertise products and services to social networks. Targeting the right audience, focusing on the right content and managing the company's budget when MAE is high, thereby boosting revenue and profits for the company is obvious, while helping to reduce labor and operating costs. MAE estimates the effectiveness of marketing activities through the use of AI for social media and advertising. When efficiency increases, it also optimizes the creation of content to reach the right audience and manages the budget for effective advertising, thereby increasing revenue, conversion rate and net profit, while cutting down on labor costs (PURCĂREA, 2024). If the business market changes, economic efficiency can help them adapt in time (Gündüzyeli, 2025). Because AI contributes to maintaining a stable source of profit, producing high-quality marketing content, helping to strengthen the brand's reputation. These support cost reduction, revenue growth, and net profit. Thus:

H5: Marketing efficiency (MAE) positively enhances the economic performance (ECP) of SMEs.

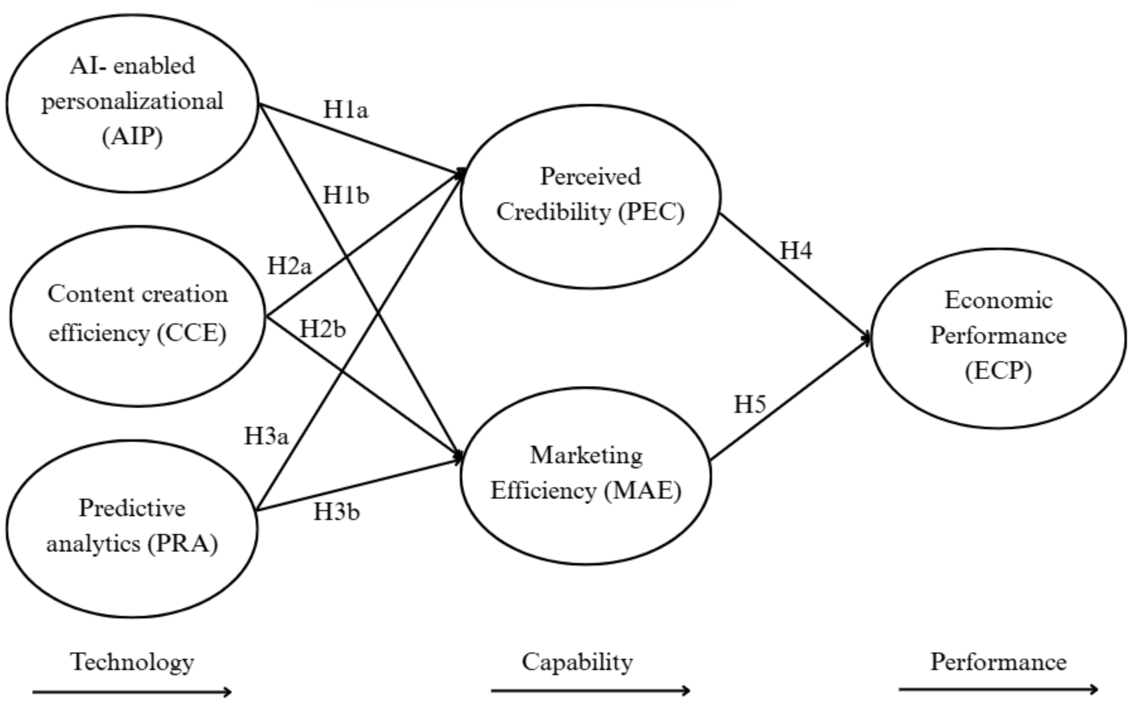

Figure 1: Conceptual model

(Source(s): Author's own work)

3. Methodology

3.1. Instrument Development and Validation

This study used a mixed method, including Delphi Study (qualitative research to explore variables) and online survey (quantitative research to test the research model). In the first phase, the research team synthesized the theoretical basis and identified important variables reflecting the impact of GenAI on marketing efficiency and economic performance of SMEs. Based on a solid theoretical foundation and referring to previous studies. The research team selected three main independent variables, representing the ability to apply GenAI in marketing. The scales of each variable were adapted from reliable academic sources and calibrated to suit the Vietnamese business context. Each variable includes 4 indicators (items), measured on a 7-point Likert scale (1 = strongly disagree, 7 = strongly agree). After building the initial measurement toolkit, 12 experts in the fields of Digital Marketing, Business Administration and AI Applications participated in the Delphi Study to assess the content validity of each scale. These experts independently assessed each question item, then the results were synthesized and analyzed through the I-CVI (Item-level Content Validity Index) and S-CVI/Ave (Scale-level Content Validity Index Average).

The results show that all variables achieved I-CVI ≥ 0.83 and S-CVI/Ave ≥ 0.90, demonstrating that the instrument has high content validity and is suitable for use in formal surveys (Ma, et al., 2022). Details are presented in Table 1 below.

Table 3. I-CVI and S-CVI/Ave Analysis

Constructs	**Items**	**Expert 1**	**Expert 2**	**Expert 3**	**Expert 4**	**Expert 5**	**Expert 6**	**Agreement**	**I-CVI**	**S-CVI/Ave**
AI-enabled Personalization (AIP)	AIP1	x	x	x	x	x	x	6	1.00	0.95
	AIP2	x	x	x	x	x	x	6	1.00	
	AIP3	x	x		x	x	x	5	0.83	
	AIP4	x	x	x	x	x		5	0.83	
Content Creation Efficiency (CCE)	CCE 1	x	x	x	x	x	x	6	1.00	0.92
	CCE 2	x	x	x		x	x	5	0.83	
	CCE 3	x	x	x	x		x	5	0.83	
	CCE 4	x	x	x	x	x	x	6	1.00	

Predictive Analytics (PRA)	PRA 1	x	x	x	x	x	x	6	1.00	0.93
	PRA 2	x	x	x		x	x	5	0.83	
	PRA 3	x	x	x	x	x		5	0.83	
	PRA 4	x	x	x	x	x	x	6	1.00	

(Source: Delphi Study conducted by the research team (2025)

3.2. Sample and Data Collection Procedures

3.2.1. Target Population and Scope

The target population of this study consists of marketing personnel, middle managers, and business owners working in SMEs in Vietnam, particularly those operating in the e-commerce, retail, and digital services sectors. These industries were selected due to their high levels of digital engagement and early adoption of GenAI applications in marketing. The sampling criteria required that participants possess practical experience or a clear understanding of integrating GenAI tools such as ChatGPT, Midjourney, or other similar platforms into their business marketing activities. The geographical scope of the study was limited to SMEs located in major urban areas, specifically Hanoi and Ho Chi Minh City, where digital transformation and the application of GenAI technologies are more prevalent. This focus ensures the relevance and reliability of insights drawn from participants who are actively engaged in technology-driven marketing environments.

3.2.2. Sampling Method

Given the limitations of time and accessibility to senior management within SMEs, this study employs a convenience sampling method. This non-probability approach was considered appropriate for reaching participants who meet the research criteria and possess relevant knowledge of GenAI applications in marketing (L.-T. Nguyen et al., 2025; N.-T. T. Nguyen et al., 2024). Data were collected through an online survey, distributed via digital platforms such as Google Forms and SurveyMonkey, which allowed for efficient and broad participation while maintaining anonymity and ease of response. Regarding sample size, the minimum required number of respondents was determined based on the analytical requirements of Partial Least Squares Structural Equation Modeling (PLS-SEM). Following the “10-times rule,” the sample should be at least ten times the maximum number of structural paths directed toward any endogenous construct in the research model. Alternatively, sample adequacy could also be verified using the G*Power formula to ensure sufficient statistical power for hypothesis testing.

3.2.3. Sample Size and Online Survey

The study collected N = 112 valid responses. This sample size is considered appropriate and ensures enough statistical power to test a complex structural model using PLS-SEM (Dang, Nguyen, & Duc, 2025; Dang, Nguyen, Tran, et al., 2025).

3.3 Measurement Scales and Instrument

This study employed a structured questionnaire to collect quantitative data for testing the research model. All constructs were measured using 7-point Likert scales, ranging from 1 (Strongly disagree) to 7 (Strongly agree), to optimize response discrimination and statistical sensitivity. The measurement items were adapted from validated studies in Al, marketing, and SME research to ensure content validity and reliability. Specifically, constructs related to generative Al were refined based on prior studies and the Delphi method to capture core functionalities relevant to SME marketing. Competency related constructs were drawn from established theoretical models of digital capabilities in SMEs, while economic performance was assessed using both non-financial and perceived financial indicators suitable for business owner and manager surveys. This approach ensures that the scales are both theoretically grounded and practically relevant, allowing for accurate measurement of the relationships in the proposed model. This section presents the scales used in the questionnaire to collect quantitative data, to test the variables and relationships in the model.

3.4. Data Analysis Method

This study employed PLS-SEM to examine and validate the proposed theoretical model. The PLS-SEM approach, executed using SmartPLS 4.0 software, was selected due to its suitability for predictive research and its ability to handle complex models with multiple constructs and mediating relationships. Unlike covariance-based SEM, PLS-SEM focuses on maximizing explained variance in the endogenous constructs and is therefore particularly appropriate for exploratory studies and models incorporating emerging technologies such as Generative Al (Henseler, 2017)

The quantitative data analysis was conducted in two main stages such as measurement and reliability testing and structural model evaluation.

3.4.1. Measurement and Reliability Testing

The first stage aimed to evaluate the reliability and validity of the measurement scales to ensure the robustness of subsequent structural analysis. Firstly, construct reliability was examined. Specifically, internal consistency reliability was assessed through Cronbach's Alpha (CA), Composite Reliability (CR), and Dijkstra-Henseler's rho_A (Dijkstra & Henseler, 2015). Following established thresholds, CA and CR values above 0.7 indicate acceptable reliability (Nunnally & Bernstein, 1994). Similarly, rho_A values greater than 0.7 confirm internal consistency among measurement items. Secondly, convergent validity was assessed through Outer Loadings and the Average Variance Extracted (AVE), each construct must be greater than 0.5, demonstrating that more than 50% of the variance is captured by the latent variable rather than by error terms (Fornell & Larcker, 1981). Thirdly, discriminant validity ensure that the constructs were conceptually distinct, discriminant validity was assessed using three approaches including the Fornell-Larcker criterion, cross-loadings, and the Heterotrait-Monotrait (HTMT) ratio (Afthanorhan, Ghazali, & Rashid, 2021). The square root of each construct's AVE should be greater than its correlation with any other construct). Additionally, all HTMT values were required to be below 0.85 (conservative threshold) or 0.90 (liberal threshold), confirming that constructs are empirically distinct (Kline, 2016).

3.4.2. Structural Model Testing Procedures

After verifying the adequacy of the measurement model, the structural model was evaluated to test the proposed hypotheses and assess the explanatory power of the model.

To begin with, multicollinearity test was determined. Prior to hypothesis testing, multicollinearity among predictor constructs was examined using the Variance Inflation Factor (VIF). All VIF values should fall between 3 and 5, indicating the absence of multicollinearity problems. Next, hypothesis Testing with path coefficients (Β), t-statistics, and p-values were generated using a bootstrapping procedure with 5,000 subsamples, following the recommendations of Hair et al. (2017). A hypothesis was accepted when t-statistics > 1.96 and p-value < 0.05, indicating statistical significance at the 95% confidence level (Chin, 1998). Then, model's predictive ability was evaluated through the Coefficient of Determination (R3), which reflects the amount of variance explained in the endogenous constructs. R^2 values of 0.75, 0.50, and 0.25 are typically considered substantial, moderate, and weak, respectively (Hair J. F., Risher, Sarstedt, & Ringle, 2019). In addition, the effect size (f) was computed to assess the contribution of each exogenous variable to the R^2 of endogenous variables, with benchmarks of 0.02 (small), 0.15 (medium), and 0.35 (large) effects (Cohen, 1988). Together, these evaluation criteria ensured that both the measurement and structural models achieved adequate reliability, validity, and explanatory power, thereby confirming the robustness of the theoretical framework.

3.5. Ethical Considerations

This study was conducted in strict adherence to established academic ethical standards to ensure integrity, transparency, and respect for participants.

First, informed consent was obtained from all participants prior to data collection. They were fully briefed on the purpose of the study, their rights, and the voluntary nature of their participation. Second, to protect confidentiality and identity, all personal information and specific details of the participating SMEs were kept strictly confidential and securely encrypted. The data were analyzed in aggregate form to ensure that neither individual nor organizational identities could be traced. Third, objectivity was maintained throughout the research process. The findings were reported truthfully and without any manipulation or distortion to align with preconceived hypotheses. Finally, the collected data were used solely for academic and research purposes within the scope of this study, ensuring that the information was not exploited for any commercial or non-academic intent.

4. Results and Discussion

4.1. Demographics

Table 4: Demographic profile of respondents

Variable	Category	Frequency	Percentage (%)
Gender	Male	40	35.7%
	Female	72	64.3%
Age	Below 26	73	65.2%
	26–35	24	21.4%
	Above 35	15	13.4%
AI Marketing Experience	Less than 6 months	52	46.4%
	6–12 months	45	40.2%
	More than 1 year	8	7.1%
Job Position	Marketing staff	74	66.1%
	Manager / Team leader	16	14.3%
	Business owner	17	15.2%

Social media platforms you often use	TikTok	44	39.3%
	Facebook	31	27.7%
	Instagram	19	17%
	Youtube	16	14.3%
Type of business	Services	43	38.4%
	Other	37	33%
	Manufacturing	22	19.6%
	Technology/IT	10	8.9%

(Source(s): Author’s own work)

According to Table 4, most participants were female about 64.3%, while males accounted for 35.7%. A big proportion of respondents were under 26 years old (65.2%), showing that the majority of GenAI employees in marketing are young professionals. Regarding AI marketing experience, 46.4% had less than six months of exposure, and 40.2% had between six months and one year, indicating that many participants are still in the early stages of adopting this technology.

In terms of job position, marketing staff made up the biggest group about 66.1%, followed by business owners around 15.2% and team leaders or managers about 14.3%. TikTok emerged as the most commonly used social media platform approximately 39.3%, followed by Facebook and Instagram around 27.7% and 17%, respectively. Concerning business types, most respondents worked in the services sector (38.4%), with a smaller share in manufacturing (19.6%) and technology (8.9%).

4.2. Common Method Bias (CMB)

Given that both indenpent and dependent constructs were collected from questionaire form, so the possibility of common method bias (CMB) should be assessed (Chin, Thatcher, & Wright, 2012). Since the dependent and independent constructs were collected from the same questionnaire, the possibility of common method bias needed to be assessed. To minimize this bias in the study, procedural and statistical measures were applied. On the procedural aspect, respondents were guaranteed complete anonymity before they participated in the survey. In addition, they were encouraged to answer honestly because there would be no right or wrong answer to the entire question. Coming to the statistical aspect, Harman's single factor test was established by using measurement items with 6 factors (AIP, CCE, PRA, PEC, MAE, and ECP) to search and explore CMB based on procedural remedies, it can be expected that no single factor accounts for more than 50% of the total variance (Wall, 2014).Therefore, common method bias is not a serious concern in this research topic.

4.3. Measurement Model Assessment

4.3.1. Construct Reliability

Table 5: Measurement model results

Constructs	Items	Loadings (FL)	Cronbach's alpha (CA)	Dijkstra Henseler's (Rho_A)	Composite reliability (CR)	Average variance extracted (AVE)	Variance Inflation factors (VIF)
AI-enabled Personalization (AIP)	AIP1	0.822	0.841	0.857	0.891	0.672	1.868
	AIP2	0.812					2.267
	AIP3	0.847					2.399
	AIP4	0.799					1.508
Content Creation Efficiency (CCE)	CCE1	0.789	0.75	0.769	0.857	0.668	1.576
	CCE2	0.886					1.837
	CCE3	0.605					1.318
	CCE4	0.772					1.384
Predictive Analytics (PRA)	PRA1	0.823	0.865	0.865	0.909	0.713	1.982
	PRA2	0.874					2.543
	PRA3	0.888					2.675
	PRA4	0.79					1.701
Perceived credibility (PEC)	PEC1	0.925	0.934	0.935	0.953	0.835	4.784
	PEC2	0.928					4.957
	PEC3	0.919					3.986
	PEC4	0.883					3.018
Marketing efficiency (MAE)	MAE1	0.825	0.793	0.808	0.865	0.615	1.624
	MAE2	0.766					1.586
	MAE3	0.811					1.657
	MAE4	0.732					1.455
Economic performance (ECP)	ECP1	0.913	0.904	0.904	0.933	0.778	3.821
	ECP2	0.923					4.008
	ECP3	0.871					2.774
	ECP4	0.817					1.843

(Source(s): Author's own work)

According to Table 5, the measurement model must be confirmed to ensure reliability and validity before testing the structural model of the factors. Based on Table 3, all constructs are acceptable because they achieve reliability, with cronbach's alpha (CA), dijkstra-Henseler's (Rho_A) and composite reliability (CR) exceeding 0.7 for all constructs in the data, so they meet the criteria for reliability.

Most of the indicators meet the requirements, however, the variable CCE3 with loadings (FL) of only 0.605 was eliminated because it was less than

0.7. In addition, the average variance extracted (AVE) value ranged from 0.615 to 0.835 (all are greater than 0.5 or 0.6), which confirms the validity.

VIF were checked and found that the values were generally below 3 and below 5, so there was no problem with this factor. After all, in general, CA, CR, AVE, pA and VIF all met the recommended thresholds, the results of this measurement model showed values with appropriate reliability for the next constructs.

4.3.2 Discriminant Validity

Table 6: Fornell – Larcker's criterion

Laten constructs	AIP	CCE	ECP	MAE	PEC	PRA
AIP	**0.820**					
CCE	0.301	**0.817**				
ECP	0.434	0.593	**0.882**			
MAE	0.321	0.591	0.735	**0.784**		
PEC	0.264	0.698	0.688	0.681	**0.914**	
PRA	0.366	0.595	0.654	0.708	0.594	**0.845**

(Source(s): Author's own work)

Based on Table 6 shows that the results of Fornell and Larcker (1981) found that the square root of AVE is higher than the correlation coefficient (Afthanorhan, Ghazali, & Rashid, 2021). In this Table 3, all the diagonal values are significantly larger than the corresponding correlation coefficients, so each concept has a lot of variance with its own indices, unlike any other factor. Therefore, the discriminant validity was confirmed very well according to the Fornell–Larcker criterion.

Table 7: Indicator loadings and cross-loadings

	AIP	CCE	ECP	MAE	PEC	PRA
AIP1	**0.822**	0.258	0.396	0.258	0.238	0.254
AIP2	**0.812**	0.156	0.345	0.225	0.147	0.235
AIP3	**0.847**	0.24	0.284	0.214	0.181	0.263
AIP4	**0.799**	0.298	0.373	0.324	0.264	0.401
CCE1	0.289	**0.789**	0.511	0.493	0.440	0.522
CCE2	0.303	**0.886**	0.573	0.552	0.654	0.562
CCE4	0.141	**0.772**	0.362	0.399	0.598	0.369

ECP1	0.407	0.485	**0.913**	0.625	0.621	0.546
ECP2	0.337	0.498	**0.923**	0.660	0.604	0.541
ECP3	0.353	0.516	**0.871**	0.606	0.571	0.579
ECP4	0.426	0.586	**0.817**	0.693	0.624	0.634
MAE1	0.344	0.626	0.691	**0.825**	0.67	0.598
MAE2	0.196	0.388	0.464	**0.766**	0.474	0.527
MAE3	0.235	0.504	0.619	**0.811**	0.602	0.568
MAE4	0.206	0.277	0.493	**0.732**	0.337	0.523
PEC1	0.209	0.675	0.648	0.610	**0.925**	0.559
PEC2	0.175	0.633	0.650	0.640	**0.928**	0.575
PEC3	0.235	0.634	0.574	0.598	**0.919**	0.450
PEC4	0.349	0.605	0.638	0.641	**0.883**	0.579
PRA1	0.230	0.457	0.540	0.623	0.481	**0.823**
PRA2	0.344	0.487	0.568	0.558	0.502	**0.874**
PRA3	0.350	0.536	0.604	0.597	0.513	**0.888**
PRA4	0.310	0.525	0.494	0.610	0.507	**0.790**

(Source(s): Author's own work)

Based on Table 7 highlight that each index has a fairly high factor loading on the structure, higher than the other structures. The factor loadings range from 0.732 to 0.888, while some indexes exceed 0.9. According to Hair et al. (2019), values greater than 0.7 are acceptable, and these values are only slightly higher than 0.9, so they can still be kept as is if this factor does not cause loading problems (Purwanto & Sudargini, Partial Least Squares Structural Squation Modeling (PLS-SEM)Analysisfor Social and Management Research : A Literature Review, 2021) . In this study, PEC2 and ECP2 with indexes of 0.928 and 0.923 respectively showed close association with their constructs and their cross-loadings were still quite low compared to the main loadings. Besides, we have the discriminant validity

Table 8: Hetero-Trait-Mono-Trait-Assessment (HTMT)

	AIP	CCE	ECP	MAE	PEC	PRA
AIP						
CCE	0.362					
ECP	0.486	0.715				

MAE	0.370	0.739	0.850		
PEC	0.286	0.824	0.746	0.770	
PRA	0.412	0.735	0.738	0.851	0.658

(Source(s): Author's own work)

We have discriminant validity between the constructs because all HTMT values are within the threshold of 0.9. In Table 8, the HTMT ratio ranges from 0.286 to 0.851, which shows that each construct is statistically different from the other constructs. For example, MAE with PRA has an index of 0.851 or ECP with MAE has an index of 0.850, which is still within the acceptable range (0.85 >HTMT<0.9) (Wong, Tan, Ooi, Lin, & Dwivedi, 2024), so the discriminant validity of this measurement model is considered to be satisfactory.

4.4. Structural Model Assessment

Table 9: Hypothesis testing

Hypotheses	Path	Original sample (O)	Sample mean (M)	Standard deviation (STDEV)	T statistics (|O/STDEV|)	P values	2.50%	97.50%	Remarks
H1b	**AIP -> MAE**	**0.047**	**0.060**	**0.080**	**0.586**	**0.558**	**-0.078**	**0.240**	**Unsupported**
H1a	**AIP -> PEC**	**0.003**	**0.016**	**0.072**	**0.041**	**0.967**	**-0.116**	**0.169**	**Unsupported**
H2b	CCE -> MAE	0.257	0.258	0.106	2.434	0.015	0.054	0.465	Supported
H2a	CCE -> PEC	0.533	0.540	0.126	4.222	0.000	0.291	0.771	Supported
H5	MAE -> ECP	0.497	0.502	0.124	4.006	0.000	0.252	0.739	Supported
H4	PEC -> ECP	0.349	0.346	0.128	2.719	0.007	0.101	0.603	Supported
H3b	PRA -> MAE	0.538	0.527	0.100	5.391	0.000	0.329	0.714	Supported
H3a	PRA -> PEC	0.276	0.258	0.128	2.153	0.031	0.023	0.514	Supported

(Source(s): Author's own work)

All hypotheses were evaluated and tested using path coefficients with t and p values to determine each relationship statistically (Kock, 2016). These relationships had p-values below 0.05, and t-values greater than 1.963 were considered statistically significant (Rouder, Morey, Speckman, & Province, 2012). Based on Table 9, the relationship between AIP and PEC (H1a) was not statistically significant with a path coefficient of 0.003, t value of 0.041, p value of 0.967, and a 2.50% index of -0.116. Similarly, the relationship between AIP and MAE (H1b) was not statistically significant with a path coefficient of 0.047, t value of 0.586, p value of 0.558, and 2.50% index of -0.078.

In contrast, CCE and PEC (H2a) showed a stronger positive relationship, with a path coefficient of 0.553, a t value of 4.222, and p = 0.000. Similarly, CCE and MAE (H2b) also showed a positive effect together (path coefficient = 0.257, t = 2.434, p = 0.015). In addition, PEA and PEC (H3a) had a strong positive effect (path coefficient = 0.276, t = 2.153, p = 0.031), and the relationship between PRA and MAE (H3b) was also statistically significant (path coefficient = 0.538, t = 0.538, and p = 0.000). Moreover, the correlations between PEC and ECP (H4) and MAE and ECP (H5) are statistically significant and positive with (path coefficient = 0.349, t = 2.719, p = 0.007) and (path coefficient = 0.497, t = 4.006, p = 0.000) respectively. This suggests that both corporate reputation and stronger marketing effectiveness strongly contribute to good economic performance.

Therefore, hypotheses H2a, H2b, H3a, H3b, H4, and H5 are supported, while H1a and H1b, on the contrary, are not supported due to a lack of statistical significance.

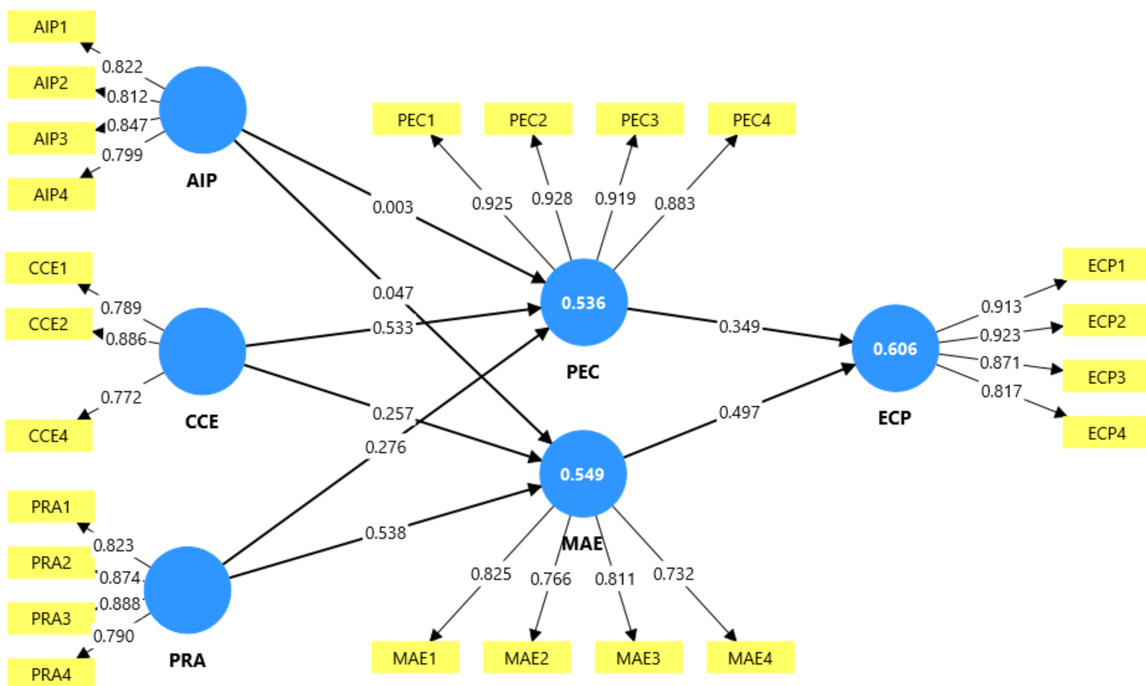

Figure 2:Hypotheses testing model

4.5. Effect size, Predictive Relevant

Table 10: Effect size (f^2)

Predictor construct/ dependent construct	ECP	MAE	PEC
AIP	0.024	0.047	0.003
CCE	0.314	0.257	0.533

ECP			
MAE	0.497		
PEC	0.349		
PRA	0.364	0.538	0.276

(Source(s): Author’s own work)

According to Table 10, this study uses Cohen's (1988) effect size (f^2) values to determine the contribution of each effect size to the dependent constructs in this structural model. According to Cohen (1988), the f^2 values of 0.02, 0.15, and 0.35 represent small, medium, and large effects, respectively, more specifically values below 0.02 indicate no effect (Gignac & Szodorai, 2016). AIP has a quite small f^2 value of 0.047 on MAE and 0.003 on PEC, which shows that this variable has a small impact on this construct, as they are lower than 0.15. This result is also justified in the hypothesis testing table when both H1a and H1b are not supported. In contrast, both CCE and PRA variables showed stronger effects (from medium to large), specifically for MAE with effect sizes of $f^2 = 0.257$ and $f^2 = 0.0.538$, respectively, while for PEC they were also $f^2 = 0.533$ and $f^2 = 0.276$, respectively. This shows their great contributions to the marketing performance and perceived credibility of SMEs. In addition, MAE (f^2 =0.497) and PEC (f^2 =0.349) both have a strong influence on ECP, so they also contribute to identifying marketing effectiveness and reliability as the main sources of high economic efficiency for SMEs in the market.

5. Implications, Conclusions and Limitations

5.1. Implications

5.1.1. Theoretical Implications

The primary contribution of this study lies in extending and empirically validating the TCP framework in the emerging context of GenAI application by SMEs in Vietnam.

The findings reveal that the mere presence of advanced Al technologies is insufficient to drive economic performance; instead, internal organizational capabilities act as the essential conduit through which technological potential is realized. Specifically, content creation efficiency and predictive analytics emerge as core Al-driven capabilities that substantially enhance both operational efficiency and brand credibility. This suggests that not all Al functionalities contribute equally to firm performance. For instance, advanced personalization may require extensive data and analytics expertise, which SMEs often lack, thereby limiting its immediate impact. This insight challenges the conventional assumption in literature that generative Al universally enhances marketing outcomes, highlighting contextual contingencies such as firm size, resource constraints, and digital maturity.

Moreover, the study confirms that organizational capabilities serve as mediators, translating technological adoption into economic performance. By uncovering these mechanisms, the research underscores the importance of a process-oriented perspective, where SMEs must not only adopt technology but also align internal processes, skillsets, and decision-making routines to harness its full potential. These theoretical contributions provide a framework for understanding why and how Al-driven interventions succeed or fail in resource-limited SMEs, offering valuable guidance for future research on emerging technologies small enterprises.

5.1.2. Managerial Implications

The findings offer clear and practical implications for managers and owners of SMEs operating in the e-commerce, retail, and digital services sectors in

Vietnam. This study strategic focus on CCE and PRA, especially SME managers should strategically prioritize investments and capacity-building initiatives in Generative AI tools that enhance CCE and PRA. Regarding CCE, the findings of this study (H2a and H2b supported) demonstrate the substantial influence of GenAI on marketing efficiency. By automating the generation of textual and visual content, firms can significantly reduce dependence on extensive creative teams, thereby lowering labor costs and accelerating marketing processes MAE. Furthermore, the ability of GenAI to deliver consistent and high-quality outputs enhances the perceived professionalism of the brand and strengthens its public image PEC. In parallel, PRA has been identified as a critical determinant of both MAE and PEC (H3a and H3b supported). The application of GenAI-driven predictive analytics enables data-driven decision-making (DDD), including accurate demand forecasting, inventory optimization, and precise customer segmentation. Consequently, this facilitates more efficient budget allocation, improved operational performance, and enhanced marketing effectiveness, thereby contributing to the overall economic performance and competitive advantage of SMEs.

Additionally, regarding capability over tools, the supported hypotheses (H4 and H5) emphasize that the adoption of GenAI alone does not guarantee improved performance; rather, the development of organizational capabilities is the key determinant of sustained effectiveness. SMEs should focus on transforming technological adoption into strategic, process-oriented competencies that integrate GenAI into daily operations. To enhance MAE, firms should standardize and automate recurring marketing processes such as post-scheduling, lead nurturing, and customer response management through GenAI. These practices enable faster response times, reduced manual workloads, and lower operational costs, thereby improving overall marketing efficiency. At the same time, building PEC requires leveraging GenAI's consistency in both content production and data-driven analysis to cultivate a professional, credible, and trustworthy brand image. A strong PEC not only reinforces customer confidence but also allows SMEs to justify higher pricing strategies and maintain a stable cash flow (ECP), ultimately strengthening their long-term economic performance.

Moreover, caution on AIP highlight that the unsupported hypotheses regarding the relationships between AIP and both PEC and MAE (H1a and H1b) suggest that AIP may not yet produce significant performance gains for SMEs. This finding underscores the need for a cautious and strategic approach to investing in highly individualized personalization technologies. SMEs, particularly those in the early stages of digital transformation, should avoid allocating excessive resources to complex personalization systems that demand advanced data infrastructure, substantial datasets, and specialized analytical expertise. Instead, managerial focus should initially center on mastering the more fundamental and high-impact applications of CCE and Predictive Analytics PRA. By first establishing operational stability and data capability through these core areas, SMEs can subsequently pursue more sophisticated personalization strategies with a higher likelihood of success and sustainable return on investment.

5.2. Conclusion

This study was conducted to test the Impact model of GenAI on marketing effectiveness and economic effectiveness of SMEs in Vietnam, based on the theoretical framework of TCP. Survey data from 112 SMEs managers and business owners were analyzed using the PLS-SEM method.

The study successfully achieved its primary objective of affirming the important role of GenAI for SMEs. The empirical model demonstrates that two technology factors are CCE and PRA - serve as core applications of GenAI, making a meaningful difference. Both factors have a positive and statistically significant impact on PEC and MAE, confirming that SMEs should prioritize the use of GenAI to automate content production and enhance data-driven decision-making. The findings also show that GenAI technology does not directly impact performance outcomes but works through capacity building. Both MAE and PEC act as key mediators that positively and directly influence ECP, suggesting that improving marketing performance and strengthening customer trust are essential pathways to converting technology adoption into tangible financial outcomes. In contrast, the hypothesis regarding AIP is not supported in this study. This suggests that, at the current stage, implementing complex personalization strategies may exceed the existing data infrastructure and operational skills of many SMEs. Therefore, AIP has yet to create a clear competitive advantage comparable to CCE and PRA.

In summary, GenAI is a cost-effective and performance lever for SMEs, but success is only achieved when businesses focus on investing in strategic CCE and PRA applications and turning them into internal capabilities to increase trust PEC and maximize MAE**.**

5.3. Directions for Future Research

This study, while robust, is subject to several limitations that suggest avenues for future research. Firstly, sampling limitation used a convenience sampling method with a sample size (n=112) primarily focused on e-commerce, retail, and digital services SMEs. Future studies should aim for a larger, more generalized sample across different sectors (e.g., manufacturing, B2B) to enhance the external validity of the findings. Secondly, cross-sectional design: The data was collected at a single point in time (cross-sectional design), which limits the ability to infer strict causality and capture the dynamic evolution of GenAI's impact. Future research could utilize a longitudinal design to track the change in MAE and ECP over time as SMEs mature in their GenAI adoption. Thirdly, model scope excluded factors related to Organizational and Environmental contexts of the TOE framework, such as organizational culture or competitive intensity. Future research should integrate these variables to understand how internal readiness and external pressures modulate the relationship between GenAI, capability, and performance. Furthermore, the research focused on investigating AIP failure that given the rejection of H1a and H1b, future research should conduct a deeper qualitative study (e.g., in-depth interviews) to explore the specific technical, data-related, or skill-based barriers that prevent SMEs in Vietnam from effectively leveraging AIP to achieve marketing efficiency.

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Appendix A: Measurement Items

AI-enabled Personalization (AIP) adopted from Chatterjee et al. (2023); Dwivedi et al. (2022)

AIP1: AI technology enables personalized customer interactions based on behavioral data.

AIP2: Generative AI allows for individualized content that increases marketing relevance.

AIP3: AI-based personalization enhances customers' trust and engagement with the brand.

AIP4: Personalized AI recommendations improve the overall customer experience.

Content Creation Efficiency (CCE) adopted from Mariani & Perez-Vega (2023); Huang & Rust (2021)

CCE1: Generative AI tools automate content generation processes effectively.

CCE2: AI-driven content creation reduces human workload and improves productivity.

CCE3: Using AI for content generation minimizes time and production costs.

CCE4: AI-generated content maintains creativity and brand alignment.

Predictive Analytics (PRA) adopted from Jeble et al. (2018); Bag et al. (2021)

PRA1: Predictive AI helps forecast future market behavior and consumer preferences.

PRA2: AI-driven analytics provides insights that improve strategic marketing decisions.

PRA3: Predictive models enhance the ability to identify profitable customer segments.

PRA4: AI-based predictions allow timely responses to changing market trends.

Marketing Efficiency (MAE) adopted from Kumar et al. (2023); Dwivedi et al. (2021)

MAE1: Generative AI supports faster decision-making in marketing operations.

MAE2: AI applications reduce marketing costs while increasing campaign effectiveness.

MAE3: The use of AI improves data-driven marketing performance.

MAE4: AI enhances coordination and efficiency in marketing activities.

Economic Performance (ECP) adopted from Dubey et al. (2020); Gupta et al. (2022)

ECP1: AI adoption contributes to higher profitability and business growth.

ECP2: Generative AI reduces operational inefficiencies and associated costs.

ECP3: AI-driven insights help improve resource utilization and cost control.

ECP4: AI adoption enhances overall firm competitiveness and long-term performance.