Research Paper

International Journal of Research and Review
[Indexed, Peer-Reviewed Journal]
Volume 13; Issue: 6; June 2026
Website: www.ijrrjournal.com
E-ISSN: 2349-9788; P-ISSN: 2454-2237

Prioritizing Critical Success Factors for Artificial Intelligence (AI) Adoption in Marketing among Small and Medium Sized Enterprises in Vietnam

Nguyen Thi Thai Ha[1]

School of Economics, Hanoi University of Industry, Hanoi, Vietnam

Corresponding Author: Nguyen Thi Thai Ha

DOI: https://doi.org/10.52403/ijrr.20260644

ABSTRACT

Artificial Intelligence (AI) has become an important driver of marketing innovation and digital transformation. However, small and medium sized enterprises (SMEs) often face resource constraints that make it difficult to identify and prioritize the factors necessary for successful AI adoption. This study aims to identify and prioritize the critical success factors for AI adoption in marketing among Vietnamese SMEs. Based on the Technology Organization Environment (TOE) framework, thirteen initial factors were identified from the literature and evaluated through a two round Delphi process involving 22 experts. Five factors were eliminated, resulting in eight validated success factors. The Fuzzy Analytic Hierarchy Process (Fuzzy AHP) was subsequently applied to determine their relative importance using expert judgments. The findings indicate that Data quality is the most important factor, followed by Leadership commitment and AI skills. These three factors account for more than 72% of the total weight, highlighting the importance of reliable data, managerial support, and organizational competencies in AI implementation. The study contributes to the AI adoption literature by providing a prioritized evaluation of success factors and extends the application of the TOE framework in the context of SMEs. The findings also offer practical guidance for managers seeking to allocate resources effectively and enhance AI adoption outcomes.

***Keywords**:* Artificial Intelligence adoption; Marketing; Small and Medium Sized Enterprises (SMEs); Critical Success Factors; TOE Framework; Fuzzy AHP.

1. INTRODUCTION

Artificial Intelligence (AI) is widely considered as one of the most transformative emerging technologies, enabling intelligent systems that can perform tasks requiring human-like learning, reasoning, and decision-making and opening new pathways for productivity, innovation, and customer engagement [1]. Recent advances in machine learning, natural language processing, predictive analytics and, more recently, generative AI have expanded the scope of AI applications across business functions, with marketing being one of the most profoundly reshaped domains. AI now supports automation, smart decision-making, customer personalization, and new value creation, and is increasingly viewed not merely as a technological tool but as a strategic enabler of competitiveness and innovation [1, 2].

AI-powered tools have fundamentally transformed contemporary marketing practice by enabling firms to deliver personalized offerings and communications, enhance interactive experiences across the customer journey, and create superior brand experiences through applications such as recommendation algorithms, dynamic pricing, automated service delivery, and content-focused advertising [2, 3].

For small and medium-sized enterprises (SMEs), which form the backbone of most economies and must overcome size-related limitations to stay competitive, AI presents transformative opportunities but also substantial challenges. SMEs can benefit from AI as much as large firms, yet adoption remains limited and often unsuccessful due to multi-dimensional barriers such as data access, skill shortages, cultural resistance and infrastructure limitations, especially in developing regions [1]. In emerging economies like Vietnam, where digital marketing and AI-powered personalization skills are rapidly expanding but accompanied by gaps, regulatory uncertainties, and uneven digital readiness, understanding how SMEs can effectively adopt AI in marketing is increasingly critical for sustainable growth and digital transformation.

Despite its potential benefits, the adoption of AI in marketing remains challenging, particularly for SMEs. Previous studies highlight numerous barriers, including limited IT infrastructure, data quality issues, financial constraints, shortages of skilled talent, cultural resistance, and difficulties assessing return on investment, which collectively slow AI uptake in smaller firms [1, 4]. In developing economies, additional obstacles such as weak institutional support, immature digital ecosystems, and regulatory and legal uncertainties further constrain successful AI adoption in SMEs [5].

Given these challenges, understanding the factors that contribute to successful AI adoption has become an important research focus. Prior work has examined AI adoption using frameworks such as TOE and Diffusion of Innovation, identifying determinants like technology compatibility, organizational culture, senior management commitment, innovation perception, and environmental pressures as key drivers and barriers for SMEs [5]. However, most of these studies emphasize whether such factors are significant rather than clarifying their relative importance or providing explicit prioritization.

In parallel, the concept of Critical Success Factors (CSFs) has gained attention for explaining successful technology implementation. CSFs represent a limited set of organizational, technological, environmental, and human conditions that must be effectively managed to achieve desired outcomes, and have been operationalized and ranked for AI adoption in specific contexts such as food supply chains using extended TOE-based frameworks and multi-criteria methods [6]. Nevertheless, AI-related CSF research remains fragmented across sectors, with diverse factor sets and only a few studies explicitly prioritizing these factors for AI adoption more generally [7].

This limitation is particularly evident in the context of SMEs operating in emerging economies. Although several studies have investigated the determinants of digital transformation and AI adoption in SMEs, relatively few have attempted to rank or prioritize critical success factors, even though SMEs face major constraints in capital, digital human resources, IT infrastructure and independent transformation capabilities, and therefore need to prioritize the most important elements when adopting new technologies [8]. Empirical evidence on such prioritization in emerging and developing markets remains scarce, even though SMEs there still struggle to adopt advanced digital technologies and many state-of-the-art tools remain untapped compared with advanced economies.

In Vietnam, AI adoption is receiving increasing attention from both policymakers and enterprises as part of the broader digital transformation agenda, with national programmes and policies launched to foster digital technologies and AI, yet many firms still face technical, financial and regulatory constraints in adopting these technologies [9].

2. LITERATURE REVIEW

2.1. Artificial Intelligence in Marketing

Artificial Intelligence (AI) has become one of the most influential technologies shaping modern marketing practices. AI refers to the ability of computer systems to perform tasks that typically require human intelligence, including learning, reasoning, problem solving, language processing, and decision making [10]. Recent advancements in machine learning, deep learning, natural language processing, and generative AI have significantly expanded the range of AI applications available to businesses [11].

In the marketing context, AI enables organizations to collect, process, and analyze large volumes of customer data, thereby improving the efficiency and effectiveness of marketing activities. AI applications are commonly used for customer segmentation, demand forecasting, recommendation systems, personalized marketing campaigns, customer relationship management, sentiment analysis, and marketing automation [12]. More recently, generative AI technologies have enabled firms to create marketing content, advertising messages, product descriptions, and customer communications with unprecedented speed and scalability [11].

For small and medium sized enterprises (SMEs), AI offers opportunities to overcome resource limitations and compete more effectively in increasingly digital markets. By leveraging AI technologies, SMEs can improve customer understanding, enhance marketing productivity, reduce operational costs, and strengthen competitive positioning. However, the successful implementation of AI requires not only technological investment but also organizational readiness and supportive external conditions.

2.2 Critical Success Factors and AI Adoption

The concept of Critical Success Factors (CSFs) was originally introduced to identify the limited number of areas in which satisfactory performance is essential for achieving organizational objectives. CSFs represent the key conditions, capabilities, and resources that determine the success of a particular initiative or strategic effort.

In technology adoption research, CSFs are frequently used to identify the factors that facilitate successful implementation of new technologies. Unlike traditional adoption studies that examine whether a factor influences adoption, CSF-oriented work seeks to understand which conditions (e.g., management support, data quality, governance, security, regulations) are most critical for successful AI adoption and to empirically rank them using structured methods such as the Analytic Hierarchy Process [7]. This distinction is particularly important for SMEs, which operate under resource constraints and need guidance on where to focus limited assets, capabilities, and commitment to increase the probability of successful AI adoption [13].

Previous studies have identified numerous factors affecting AI adoption, including technological readiness, resources, culture, leadership support, and external pressures, and have shown that aspects such as relative advantage, top management support, cost-effectiveness, competitive pressure, vendor support, compatibility, strategic alignment and resource availability significantly shape organizational intentions to adopt AI-based technologies [14]. However, even recent reviews emphasize that, although many individual, social, technological, organizational and environmental determinants have been identified, research is still developing and further work is needed to understand and structure these factors, including their interrelationships and influence on outcomes [15].

2.3 Technology Organization Environment (TOE) Framework

The Technology Organization Environment (TOE) framework developed by Tornatzky and Fleischer (1990) [16] is one of the most widely used theoretical frameworks for studying organizational technology adoption. The framework suggests that technology adoption is influenced by three contextual dimensions: technology, organization, and environment.

The technology context refers to the technological resources and capabilities available to an organization. These include technological infrastructure, system compatibility, data quality, technological complexity, and other technology related characteristics that influence adoption decisions.

The organization context encompasses internal organizational characteristics such as leadership support, employee competencies, organizational culture, financial resources, and managerial capabilities. These factors determine an organization's ability to implement and utilize new technologies effectively.

The environment context includes external factors surrounding the organization, such as competitive pressure, government regulations, industry conditions, technology vendors, and relationships with external stakeholders. These environmental conditions can either facilitate or hinder technology adoption.

The TOE framework is particularly suitable for the present study because it provides a comprehensive perspective for examining the multidimensional factors influencing AI adoption in SMEs. Furthermore, the framework has been widely applied in studies of digital transformation, cloud computing, big data analytics, artificial intelligence, and other emerging technologies.

2.4 Previous Studies on Critical Success Factors for AI Adoption

The growing interest in AI adoption has generated a substantial body of research examining the factors that contribute to successful implementation. Existing studies indicate that AI adoption success depends on a combination of technological, organizational, and environmental conditions, and have begun to identify and prioritize critical success factors such as management support, data quality, data governance and regulatory aspects across multi-stage AI adoption models [7].

From a technological perspective, studies consistently emphasize the importance of data quality, technological infrastructure, and system integration capabilities, highlighting data quality and technological infrastructure as critical readiness factors for AI adoption [17].

From an organizational perspective, leadership commitment and senior management support are repeatedly identified as highly influential, together with technical competencies, resources, organizational compatibility and culture [5, 18].

From an environmental perspective, competitive pressure, government support or regulation, and vendor or ecosystem support emerge as important external drivers and constraints of AI adoption for organizations, including SMEs [14] [19].

Despite these findings, the literature on AI adoption in SMEs is described as fragmented, with heterogeneous factor sets and notable gaps, particularly regarding environmental aspects and systematic prioritization of factors for SMEs [5].

2.5 Development of Initial Success Factors Based on TOE

Based on the TOE framework and previous literature, this study develops an initial set of success factors for AI adoption in marketing. These factors are classified into three categories corresponding to the technological, organizational, and environmental dimensions of the TOE framework.

Technology Factors

Data quality: The extent to which customer and marketing data used by AI systems are accurate, complete, and correct; high-quality data are essential because AI models must be trained on good data to generate reliable results and useful predictions [13].

IT infrastructure: The underlying technological foundation that supports AI implementation, including storage, networking, and scalable computing capabilities needed to handle data-intensive AI workloads and enable training and operation of AI models [13].

System integration: The capability to link AI applications with existing information systems and data sources so that data can flow smoothly from its origin to AI models and back into business processes, supported by defined data pipelines and automated data streams [13].

AI tool reliability: The degree to which AI systems perform their intended functions without failure over a given period and under expected conditions, so that they can be used with confidence in real-world decision-making [20].

Organization Factors

Leadership commitment: The extent to which senior management actively supports AI initiatives through strategic direction, resource allocation, and organizational encouragement. Strong leadership commitment is essential for driving AI adoption and organizational change [14].

AI skills: The knowledge, competencies, and technical capabilities required to implement, manage, and utilize AI technologies effectively within marketing activities. Adequate AI skills enable organizations to maximize the value of AI investments [18].

Employee readiness: The willingness and preparedness of employees to adopt AI technologies and adapt to new work processes. Higher levels of readiness facilitate smoother implementation and reduce resistance to change [21].

Innovation culture: The organizational values, beliefs, and norms that encourage experimentation, learning, creativity, and technological innovation. A strong innovation culture supports the successful adoption of emerging technologies [22].

Financial resources: The availability of financial capital required to invest in AI technologies, employee training, infrastructure development, and organizational transformation initiatives [23].

Environment Factors

Competitive pressure: The influence of market competition on an organization's decision to adopt AI technologies; intense competition often drives firms to adopt AI in order to reduce costs, outperform rivals, and secure or enhance competitive advantage [14].

Government support: The policies, incentives, regulatory frameworks, and other public measures provided by governmental agencies that create a supportive environment for AI and digital technologies, such as subsidies or tax incentives that positively promote enterprises' digital transformation [24].

Technology vendor support: The technical assistance, consulting, training, and implementation services offered by AI solution providers that help organizations address skill gaps and overcome issues encountered when using AI, making vendor support a key predictor of AI adoption [14].

External collaboration: The partnerships and cooperative relationships with technology providers, consultancies, research institutions, industry consortia, and government agencies that enable organizations to access external expertise, robust infrastructure, and best practices, thereby accelerating AI adoption and ensuring alignment with organizational goals and regulations [25]

2.6. Research Framework

Based on the TOE framework, the proposed research framework consists of three primary dimensions: Technology, Organization, and Environment. These dimensions encompass thirteen initial success factors that are expected to influence the successful adoption of AI in marketing among Vietnamese SMEs. The Delphi method will subsequently be used to validate and refine these factors, while the Analytic Hierarchy Process (AHP) will be employed to determine their relative importance and priority rankings.

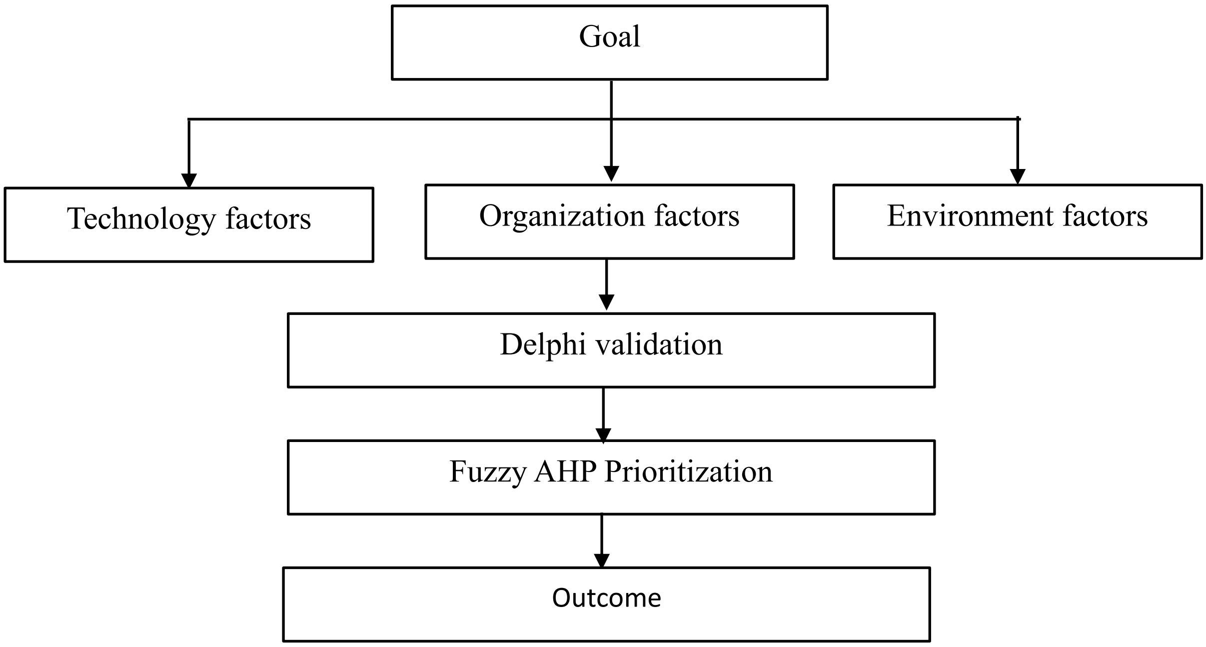

Figure 1. Proposed Research Framework

3. MATERIALS AND METHODS

3.1 Delphi Method

The Delphi method is a systematic and iterative technique used to obtain consensus among experts on complex research issues [26]. The method relies on multiple rounds of consultation with a panel of experts, allowing participants to review, revise, and refine their judgments based on controlled feedback from previous rounds. By maintaining anonymity among experts, the Delphi method minimizes the influence of dominant individuals and group pressure, thereby enhancing the reliability and objectivity of the consensus-building process [27].

In studies involving emerging technologies such as Artificial Intelligence (AI), Delphi is particularly valuable because empirical evidence is often limited and expert knowledge plays a critical role in identifying relevant success factors [28]. Through iterative evaluation, experts assess the relevance and necessity of each proposed factor, while factors receiving insufficient agreement may be revised or eliminated. This process ensures that the final set of factors reflects both theoretical foundations and practical considerations [29].

In this study, the Delphi method was employed to validate and refine the initial success factors identified from the literature review. A panel of experts from academia and industry evaluated the proposed factors through two Delphi rounds. The Content Validity Ratio (CVR) proposed by Lawshe (1975) [30] was used to assess the level of expert consensus. Factors failing to achieve the minimum CVR threshold were excluded from subsequent analysis, while the remaining factors were retained for prioritization using Fuzzy AHP.

3.2. Fuzzy Analytic Hierarchy Process (Fuzzy AHP)

Following factor validation, the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) was employed to determine the relative importance of the validated success factors. Developed from the traditional

Analytic Hierarchy Process introduced by Saaty (2004) [31], Fuzzy AHP integrates fuzzy set theory to address the uncertainty and ambiguity inherent in human judgments [32]. Unlike conventional AHP, which relies on precise numerical comparisons, Fuzzy AHP allows experts to express preferences using linguistic terms that are subsequently converted into fuzzy numbers. This approach provides a more realistic representation of subjective assessments and improves the robustness of decision-making outcomes.

Fuzzy AHP has been widely applied in technology adoption, digital transformation, and strategic management studies because it effectively captures the uncertainty associated with expert evaluations. In the context of AI adoption, where many factors involve qualitative judgments and incomplete information, Fuzzy AHP offers a suitable mechanism for deriving reliable priority weights.

The Fuzzy AHP procedure adopted in this study consisted of four main steps:

1. Constructing the hierarchical structure consisting of the research goal, the three TOE dimensions (Technology, Organization, and Environment), and the validated success factors.
2. Conducting pairwise comparisons among dimensions and factors using linguistic scales represented by triangular fuzzy numbers.
3. Calculating fuzzy synthetic extent values and deriving normalized weights for each dimension and factor using Chang's extent analysis method [32].
4. Defuzzifying the fuzzy weights and ranking the success factors according to their relative importance.

To ensure the reliability of expert judgments, consistency analysis was performed prior to the fuzzy calculations. The resulting weights were subsequently used to establish the final priority ranking of critical success factors influencing AI adoption in marketing among Vietnamese SMEs. The Fuzzy AHP approach provides a comprehensive and rigorous evaluation framework by accommodating the uncertainty of expert opinions while generating meaningful priority rankings for managerial decision making.

4. Data collection and analysis

Primary data were collected from a panel of experts academics, AI specialists, digital marketing professionals, business consultants, and SME managers with experience in Artificial Intelligence (AI) adoption, digital transformation, or marketing technology implementation. The Delphi survey was conducted in two rounds to validate and refine the initial success factors identified through the literature review. Experts evaluated the relevance and necessity of each factor, and the Content Validity Ratio (CVR) was used to assess the level of consensus and determine factor retention.

Following the Delphi process, pairwise comparison questionnaires were administered to a selected group of experts to evaluate the relative importance of the validated factors. Linguistic judgments were converted into triangular fuzzy numbers to accommodate uncertainty and subjectivity in expert assessments. Secondary data, including academic publications, industry reports, and policy documents related to AI adoption and digital transformation, were used to support the development of the research framework and interpretation of the findings. The integration of literature review, Delphi validation, and Fuzzy AHP weighting provides a comprehensive basis for identifying and prioritizing the critical success factors influencing AI adoption in marketing among Vietnamese SMEs.

4.1 The Delphi results

The Delphi method was employed to validate the relevance and contextual suitability of the proposed success factors for Artificial Intelligence (AI) adoption in marketing among Vietnamese SMEs. A panel of 22 experts participated in two rounds of Delphi evaluation to assess the necessity of the factors identified from the literature review.

In the first round, the experts evaluated thirteen initial factors. Based on the obtained Content Validity Ratio (CVR) values, four factors, namely AI tool reliability, Competitive pressure, Government support, and External collaboration, were removed due to insufficient consensus. The remaining factors were subsequently reassessed in the second round.

The second round demonstrated a higher level of agreement among the experts. However, Innovation culture did not meet the minimum CVR threshold of 0.42 and was therefore excluded from the final framework. As a result, eight factors were retained for the subsequent Fuzzy AHP analysis. All retained factors achieved CVR values equal to or greater than the required threshold, indicating satisfactory expert consensus regarding their importance for successful AI adoption in marketing.

Table 1: Results of the Delphi Method

No.	Criteria	Round 1			Round 2			Accepted /Rejected
		Average	Ne	CVR	Average	Ne	CVR	
1	Data quality	4.55	19	0.73	4.50	20	0.82	Accepted
2	IT infrastructure	4.32	19	0.73	4.27	18	0.64	Accepted
3	System integration	4.23	18	0.64	4.32	19	0.73	Accepted
4	AI tool reliability	3.73	12	0.09				Rejected
5	Leadership commitment	4.59	21	0.91	4.55	21	0.91	Accepted
6	AI skills	4.32	20	0.82	4.41	20	0.82	Accepted
7	Employee readiness	4.23	17	0.55	4.14	18	0.64	Accepted
8	Innovation culture	3.95	17	0.55	3.95	14	0.27	Rejected
9	Financial resources	4.14	18	0.64	4.09	18	0.64	Accepted
10	Competitive pressure	3.64	12	0.09				Rejected
11	Government support	3.86	15	0.36				Rejected
12	Technology vendor support	4.23	18	0.64	4.18	17	0.55	Accepted
13	External collaboration	3.86	13	0.18				Rejected

4.2 Fuzzy set

In decision making and evaluation processes, expert judgments are often characterized by uncertainty, vagueness, and imprecision, making it difficult to express preferences using exact numerical values. Traditional quantitative approaches may therefore fail to capture the complexity of human reasoning. To overcome this limitation, fuzzy set theory provides a flexible framework that allows evaluators to express their opinions through linguistic assessments rather than precise numbers [33]. These linguistic evaluations can subsequently be transformed into fuzzy numbers, enabling qualitative judgments to be analyzed mathematically. Among various fuzzy representations, triangular fuzzy numbers (TFNs) are widely adopted because of their computational simplicity and effectiveness in handling subjective assessments [34]. A triangular fuzzy number, denoted as A = (l, m, u), is represented by a membership function μA(x), as presented in Equation (1).

$$u_{\bar{A}}(x) : R \to [0,1]\left(0 \le u_{\bar{A}}(x) \le 1, x \in X\right)$$

$$u_{\bar{A}}(x) = \begin{cases} 0 & \text{for } x < 1 \\ \dfrac{x-1}{m-1} & \text{for } 1 \le x \le m \\ \dfrac{u-x}{u-m} & \text{for } m \le x \le u \\ 0 & \text{for } x > u \end{cases}$$

4.3 Fuzzy AHP

Step 1: Constructing the Hierarchical Structure

The hierarchical structure consists of three levels:

Level 1: The research goal, namely prioritizing the critical success factors for AI adoption in marketing among Vietnamese SMEs.

Level 2: The three TOE dimensions, including Technology, Organization, and Environment.

Level 3: The validated success factors under each dimension: Data quality, IT infrastructure, System integration, Leadership commitment, AI skills, Employee readiness, Financial resources, and Technology vendor support.

This hierarchical structure serves as the basis for subsequent pairwise comparisons and weight calculations in the Fuzzy AHP analysis.

Step 2: Constructing the pairwise comparison matrix and consistency check

Following the development of the hierarchical structure, pairwise comparison matrices were constructed to evaluate the relative importance of the TOE dimensions and the validated success factors. Experts were asked to compare each element with every other element using Saaty's nine point scale, ranging from 1 (equal importance) to 9 (extreme importance). The collected judgments were then organized into pairwise comparison matrices for subsequent analysis.

To ensure the reliability and logical consistency of expert evaluations, a consistency ratio (CR) test was performed for each comparison matrix. Consistency assessment is an essential step in the AHP methodology because inconsistent judgments may reduce the credibility of the resulting priorities [31]. According to Saaty (2004) [31], a comparison matrix is considered acceptable when the calculated CR value does not exceed 0.10. If the CR exceeds the recommended threshold, the corresponding judgments should be reviewed and revised to improve consistency. Maintaining an acceptable consistency level ensures that the derived weights accurately reflect experts' preferences and provides a reliable basis for prioritizing the critical success factors. The consistency ratio was calculated using the following equations:

$$CR = \frac{CI}{RI} \qquad (2)$$

$$CI = \frac{\lambda_{\max} - n}{n-1}$$

Where: λ_{max} denotes the maximum eigenvalue of the comparison matrix

n represents the number of criteria.

The random consistency index (RI) varies according to matrix size, and the corresponding values are provided in table 2.

Table 2: The random consistency index (RI) values corresponding to the number of criteria.

Number of criteria (n)	**1**	**2**	**3**	**4**	**5**	**6**	**7**	**8**	**9**	**10**
Random Consistency Index (RI)	0.00	0.00	0.58	0.90	1.12	1.24	1.32	1.41	1.45	1.49

If the calculated CR exceeded the acceptable threshold of 0.10, the corresponding expert judgments were re-examined and revised until the consistency condition was satisfied.

Step 3: Constructing the Fuzzy Pairwise Comparison Matrix

A conversion scale is applied to transform linguistic variables into fuzzy numbers. This study adopts the 1-9 scale proposed by Kahraman et al. (2004) [35], with five conversion intervals as presented in Table 3.

Table 3. Linguistic Variables and Their Corresponding Fuzzy Numbers

Linguistic term	**Crisp scale**	**Fuzzy triangular number (l, m, u)**	**Reciprocal fuzzy number (1/u, 1/m, 1/l)**
Equally important	1	(1, 1, 1)	(1/1, 1/1, 1/1)
Moderately more important	3	(2, 3, 4)	(1/4, 1/3, 1/2)
Strongly more important	5	(4, 5, 6)	(1/6, 1/5, 1/4)
Very strongly more important	7	(6, 7, 8)	(1/8, 1/7, 1/6)
Extremely more important	9	(8, 9, 9)	(1/9, 1/9, 1/8)

Assume that there are k experts evaluating the relative importance of the criteria. Based on the fuzzy geometric mean, the aggregated value of each criterion $\tilde{a}_{ij}$ is calculated as follows:

$$\tilde{a}_{ij} = \left(\prod_{k=1}^{K} \tilde{a}_{ij}^{k} \right)^{\frac{1}{K}} \quad (3)$$

In which:
$\tilde{a}_{ij}$ is the fuzzy geometric mean of the criterion,
k is the number of experts involved in the evaluation.
From this, the fuzzy pairwise comparison matrix is constructed as follows:

$$A = \begin{bmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ \tilde{a}_{21} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \tilde{a}_{n1} & \tilde{a}_{n2} & \dots & 1 \end{bmatrix} = \begin{bmatrix} 1 & \tilde{a}_{12} & \dots & \tilde{a}_{1n} \\ 1/\tilde{a}_{12} & 1 & \dots & \tilde{a}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ 1/\tilde{a}_{1n} & 1/\tilde{a}_{2n} & \dots & 1 \end{bmatrix} \quad (4)$$

Step 4: Calculation of fuzzy weights for each criterion

The geometric mean method is employed to determine the fuzzy geometric mean and the fuzzy weight for each criterion.

$$\tilde{r}_j = (\tilde{a}_{i1} \times \tilde{a}_{i2} \times \tilde{a}_{i3} \times \ldots \times \tilde{a}_{in})^{1/n} \quad (5)$$

$$\tilde{w}_j = \tilde{r}_j \times (\tilde{r}_1 + \tilde{r}_2 + \ldots + \tilde{r}_i + \ldots + \tilde{r}_n)^{-1} \quad (6)$$

In which:
r_j is the fuzzy geometric mean,
$\tilde{w}_j$ is the fuzzy weight of the j[th] criterion.

With $\tilde{w}_j$ =(L_{wj},M_{wj},U_{wj}), where L_{wj}, M_{wj} and U_{wj} represent the lower, middle, and upper values of the fuzzy weight of the j[th] criterion, respectively.

Step 5: Defuzzification of fuzzy weights

Since $\tilde{w}_j$ is still a fuzzy number, defuzzification is performed using the Centre of Area (COA) method, according to the following formula:

$$\overline{w}_j = \frac{L_{w_j} + M_{w_j} + U_{w_j}}{3} \quad (7)$$

In which: $\overline{w}_j$ is the actual weight of the j[th] criterion.

Step 6: Converting $\bar{w}_j$ into weight form

The conversion of $\bar{w}_j$ into the weight w_j is calculated according to the following formula:

$$\mathrm{w}_j = \frac{\bar{w}_j}{\sum_{i=1}^{n} \bar{w}_j} \qquad (8)$$

In which:

$\bar{w}_j$ is the actual weight of the jth criterion,

n is the total number of criteria.

After obtaining the normalized weights, the relative importance of all criteria can be determined and ranked accordingly. The resulting weights indicate the contribution of each criterion to the overall objective and provide a basis for identifying the most critical success factors. Criteria with higher weights are considered more influential and therefore deserve greater managerial attention and resource allocation. Consequently, the final ranking derived from the Fuzzy AHP analysis enables decision makers to distinguish between primary and secondary factors and to prioritize strategic actions more effectively.

5. Research findings

Step 1: Constructing the Hierarchical Structure

Based on the literature review and the Delphi validation results, a hierarchical structure was developed to prioritize the critical success factors for AI adoption in marketing among Vietnamese SMEs. The final framework consists of three TOE dimensions, namely Technology, Organization, and Environment, encompassing eight validated success factors: Data quality, IT infrastructure, System integration, Leadership commitment, AI skills, Employee readiness, Financial resources, and Technology vendor support.

To conduct the Fuzzy AHP analysis, pairwise comparison judgments were collected from five experts with extensive experience in AI applications, digital transformation, marketing management, and SME development. Their evaluations served as the basis for determining the relative importance of the dimensions and success factors.

Step 2: Constructing the Pairwise Comparison Matrix and Consistency Check

Pairwise comparison matrices were constructed based on the judgments provided by five experts with extensive experience in AI applications, digital transformation, and marketing management. These experts were selected from the panel that participated in the Delphi process. They evaluated the relative importance of the TOE dimensions and the validated success factors using Saaty's pairwise comparison scale.

To ensure the reliability of the evaluations, the consistency ratio (CR) was calculated for each comparison matrix. The results indicated that all CR values were below the recommended threshold of 0.10 ($CR < 0.10$), confirming the logical consistency and reliability of the expert judgments.

Step 3: In this step, the Fuzzy Analytic Hierarchy Process (Fuzzy AHP) was applied to determine the relative importance of the TOE dimensions and the validated success factors. The pairwise comparison judgments provided by the five experts were first converted into triangular fuzzy numbers using the predefined linguistic scale. Subsequently, the fuzzy geometric mean method was employed to aggregate the individual comparison matrices into a single fuzzy pairwise comparison matrix, representing the collective judgment of the expert panel. This aggregated matrix served as the foundation for calculating the fuzzy weights and priority rankings of the critical success factors.

Table 4: The pairwise comparison matrix

Criteria	Data quality	IT infrastructure	System integration	Leadership commitment	AI skills	Employee readiness	Financial resources	Technology vend support
Data quality	(1, 1, 1)	(3.031, 4.076, 5.102)	(4.704, 5.720, 6.732)	(1.149, 1.246, 1.320)	(1.741, 2.408, 3.031)	(8, 9, 9)	(6.732, 7.740, 8.386)	(8, 9, 9)
IT infrastructure	(0.196, 0.245, 0.330)	(1, 1, 1)	(1.149, 1.246, 1.320)	(0.330, 0.415, 0.574)	(0.758, 0.803, 0.871)	(3.031, 4.076, 5.102)	(1.741, 2.408, 3.031)	(4.704, 5.720, 6.732)
System integration	(0.149, 0.175, 0.213)	(0.758, 0.803, 0.871)	(1, 1, 1)	(0.196, 0.245, 0.330)	(0.330, 0.415, 0.574)	(1.741, 2.408, 3.031)	(1.149, 1.246, 1.320)	(3.031, 4.076, 5.102)
Leadership commitment	(0.758, 0.803, 0.871)	(1.741, 2.408, 3.031)	(3.031, 4.076, 5.102)	(1, 1, 1)	(1.149, 1.246, 1.320)	(6.732, 7.740, 8.386)	(4.704, 5.720, 6.732)	(8, 9, 9)
AI skills	(0.330, 0.415, 0.574)	(1.149, 1.246, 1.320)	(1.741, 2.408, 3.031)	(0.758, 0.803, 0.871)	(1, 1, 1)	(4.704, 5.720, 6.732)	(3.031, 4.076, 5.102)	(6.732, 7.740, 8.386)
Employee readiness	(0.111, 0.111, 0.125)	(0.196, 0.245, 0.330)	(0.330, 0.415, 0.574)	(0.119, 0.129, 0.149)	(0.149, 0.175, 0.213)	(1, 1, 1)	(0.758, 0.803, 0.871)	(1.149, 1.246, 1.320)
Financial resources	(0.119, 0.129, 0.149)	(0.330, 0.415, 0.574)	(0.758, 0.803, 0.871)	(0.149, 0.175, 0.213)	(0.196, 0.245, 0.330)	(1.149, 1.246, 1.320)	(1, 1, 1)	(1.741, 2.408, 3.031)
Technology vendor support	(0.111, 0.111, 0.125)	(0.149, 0.175, 0.213)	(0.196, 0.245, 0.330)	(0.111, 0.111, 0.125)	(0.119, 0.129, 0.149)	(0.758, 0.803, 0.871)	(0.330, 0.415, 0.574)	(1, 1, 1)

Step 3-6: Formulas (5)–(8) are applied to compute the fuzzy coefficient $\tilde{r}_j$, the fuzzy weight $\tilde{w}_j$, the normalized fuzzy weight $\bar{w}_j$, and the final crisp weight wj. The calculation results are presented in Table 5.

Table 5: Application of Fuzzy AHP for Criterion Weight Determination

Criterions	Fuzzy coefficient $\tilde{r}_j$	Value	Fuzzy weight $\tilde{w}_j$	Value	Normalized weight $\bar{w}_j$	Value	Crisp weight w_j	Value	Rank
Data quality	$\tilde{r}_1$	(3.245, 3.804, 4.181)	$\tilde{w}_1$	(0.279, 0.392, 0.472)	$\bar{w}_1$	0.381	w_1	0.3202	1
IT infrastructure	$\tilde{r}_2$	(1.043, 1.243, 1.477)	$\tilde{w}_2$	(0.090, 0.128, 0.167)	$\bar{w}_2$	0.128	w_2	0.1077	4
System integration	$\tilde{r}_3$	(0.677, 0.804, 0.959)	$\tilde{w}_3$	(0.058, 0.083, 0.108)	$\bar{w}_3$	0.083	W_3	0.0699	5
Leadership commitment	$\tilde{r}_4$	(2.417, 2.812, 3.122)	$\tilde{w}_4$	(0.208, 0.290, 0.353)	$\bar{w}_4$	0.283	w_4	0.2382	2
AI skills	$\tilde{r}_5$	(1.623, 1.914, 2.213)	$\tilde{w}_5$	(0.140, 0.197, 0.250)	$\bar{w}_5$	0.196	w_5	0.1644	3
Employee readiness	$\tilde{r}_6$	(0.320, 0.355, 0.414)	$\tilde{w}_6$	(0.028, 0.037, 0.047)	$\bar{w}_6$	0.037	w_6	0.0311	7
Financial resources	$\tilde{r}_7$	(0.452, 0.522, 0.617)	$\tilde{w}_7$	(0.039, 0.054, 0.070)	$\bar{w}_7$	0.054	w_7	0.0455	6
Technology vendor support	$\tilde{r}_8$	(0.239, 0.263, 0.308)	$\tilde{w}_8$	(0.021, 0.027, 0.035)	$\bar{w}_8$	0.027	w_8	0.0231	8

The results show that Data quality received the highest priority weight (0.3202), followed by Leadership commitment (0.2382) and AI skills (0.1644). These three factors account for more than 72% of the total weight, indicating their dominant importance in supporting AI adoption in marketing among Vietnamese SMEs. In contrast, Technology vendor support (0.0231), Employee readiness (0.0311), and financial resources (0.0455) received the lowest weights. Based on the obtained rankings, the critical success factors can be prioritized in the following order: Data quality, leadership commitment, AI skills, IT infrastructure, system integration, financial resources, employee readiness, and technology vendor support.

6. DISCUSSION

The findings reveal that Data quality is the most critical success factor for AI adoption in marketing among Vietnamese SMEs, followed by Leadership commitment and AI skills. Together, these three factors account for more than 72% of the total weight, indicating that successful AI implementation depends primarily on the availability of reliable data, strong managerial support, and sufficient organizational competencies. The results suggest that SMEs should prioritize building a solid data foundation before investing heavily in advanced AI applications.

The prominence of Data quality is consistent with previous studies emphasizing that AI systems rely heavily on accurate, complete, and timely data to generate meaningful predictions and marketing insights [36]. Poor-quality data can reduce model accuracy, increase operational risks, and undermine decision-making effectiveness. As AI applications in marketing depend extensively on customer information, behavioral data, and market analytics, the quality of data becomes a prerequisite for successful adoption.

Leadership commitment emerged as the second most important factor. This finding supports earlier research highlighting the central role of top management support in technology adoption and digital transformation initiatives [37]. In SMEs, where strategic decisions are often concentrated among a small group of managers, leadership commitment influences resource allocation, organizational priorities, and employees' willingness to embrace AI-related changes. Strong managerial support therefore helps reduce uncertainty and facilitates the implementation process.

AI skills ranked third, confirming the importance of human capital in AI adoption. This result aligns with prior studies arguing that organizations require employees with sufficient technical knowledge and analytical capabilities to utilize AI effectively [19, 38, 39]. Even when AI technologies are available, firms may fail to realize their potential if employees lack the competencies necessary to operate, interpret, and integrate AI-generated outputs into marketing activities.

The findings can be interpreted through the Technology Organization Environment (TOE) framework. Within the technology dimension, Data quality, IT infrastructure, and System integration collectively represent the technological readiness required for AI adoption. The highest ranking of Data quality indicates that technological resources alone are insufficient unless supported by reliable and accessible data. Within the organizational dimension, Leadership commitment and AI skills received substantially higher weights than Employee readiness and Financial resources, suggesting that managerial capability and organizational knowledge are perceived as more important than resource availability. Within the environmental dimension, Technology vendor support received the lowest priority, indicating that SMEs place greater emphasis on internal capabilities than on external assistance when adopting AI in marketing.

The results can also be explained through the Dynamic Capabilities Theory [40]. Dynamic capabilities emphasize an organization's ability to sense opportunities, seize opportunities, and reconfigure resources in response to environmental changes. The highest-ranked factor, Data quality, directly supports sensing opportunities by enabling firms to identify customer needs, market trends, and emerging patterns through data-driven insights. Leadership commitment contributes primarily to seizing opportunities because managers play a decisive role in recognizing the strategic value of AI and mobilizing organizational resources to exploit it. AI skills facilitate both sensing and seizing activities by allowing employees to transform data into actionable knowledge and apply AI technologies effectively in marketing operations.

Furthermore, IT infrastructure and System integration support the reconfiguring resources capability by enabling organizations to connect data sources, integrate AI tools into existing systems, and redesign business processes. Financial resources also contribute to reconfiguration by providing the investments necessary for technological upgrades and organizational transformation. Although Technology vendor support received the lowest weight, it still plays a complementary role by supplying external expertise and implementation assistance during the transformation process.

Overall, the findings suggest that successful AI adoption in marketing among Vietnamese SMEs is driven primarily by internal technological and organizational capabilities rather than external support mechanisms. The results reinforce the argument that SMEs should focus first on building high-quality data assets, strengthening managerial commitment, and developing AI-related competencies before expanding investments in more advanced AI applications.

7. CONCLUSION

This study aimed to identify and prioritize the critical success factors for Artificial Intelligence (AI) adoption in marketing among Vietnamese small and medium-sized enterprises (SMEs). By integrating the Delphi method and Fuzzy Analytic Hierarchy Process (Fuzzy AHP) within the Technology Organization Environment (TOE) framework, the study systematically evaluated the relative importance of factors influencing AI adoption. Through two rounds of Delphi consultation with 22 experts, the initial list of thirteen factors was refined to eight validated success factors. Subsequently, Fuzzy AHP was employed to determine their priority rankings.

The findings indicate that Data quality is the most critical success factor, followed by Leadership commitment and AI skills. Together, these three factors account for more than seventy percent of the total weight, highlighting their dominant role in enabling successful AI adoption in marketing. The results suggest that AI implementation is not primarily constrained by external support or financial considerations, but rather by the availability of high-quality data, strong managerial commitment, and sufficient organizational capabilities. IT infrastructure and System integration were also found to be important, although their influence was lower than that of the top-ranked factors. In contrast, Employee readiness, Financial resources, and Technology vendor support received relatively lower priority weights.

From a theoretical perspective, this study contributes to the AI adoption literature by moving beyond the traditional examination of adoption determinants and providing a systematic prioritization of critical success factors. While previous studies have largely focused on identifying factors associated with AI adoption, relatively few have investigated their relative importance, particularly in SMEs operating in emerging economies. The study also extends the application of the TOE framework by demonstrating how technological, organizational, and environmental factors differ in their contribution to AI adoption success. Furthermore, the findings complement Dynamic Capabilities Theory by showing that the highest-ranked factors support firms' abilities to sense opportunities through data, seize opportunities through leadership commitment, and reconfigure resources through technological and human capabilities.

The study also offers practical implications for SME managers and decision makers. Given limited resources, SMEs should prioritize investments in data management practices, data governance, and data quality improvement initiatives before pursuing advanced AI applications. At the same time, senior managers should actively support AI initiatives by providing strategic direction, allocating resources, and fostering organizational commitment. Developing AI-related competencies among employees should also be considered a strategic priority, as technical skills are essential for translating AI investments into business value. By focusing on these areas, SMEs can improve the effectiveness of AI adoption and enhance their marketing performance.

Despite its contributions, this study has several limitations. First, the findings are based on expert judgments rather than large-scale organizational survey data, which may limit generalizability. Second, the study focuses exclusively on Vietnamese SMEs and may not fully capture conditions in other countries or industries. Third, the prioritization results reflect expert perceptions at a specific point in time and may evolve as AI technologies continue to develop.

Future research may address these limitations by conducting empirical studies involving larger samples of SMEs and testing the relationships between the identified factors and actual AI adoption outcomes. Comparative studies across industries or countries could provide additional insights into contextual differences. Future researchers may also integrate other theoretical perspectives and multi-criteria decision-making methods to further explore the dynamic and evolving nature of AI adoption in organizations.

Declaration by Authors

Acknowledgement: None

Source of Funding: None

Conflict of Interest: No conflicts of interest declared.

REFERENCES

1. Sánchez Alcalde E, Calderón Cuadrado MR, Herrera Triguero F. Artificial intelligence adoption in SMEs: Survey based on TOE–DOI framework, primary methodology and challenges. 2025. https://doi.org/10.3390/app15126465
2. Kumar V, Ramachandran D, Kumar B. Understanding the role of artificial intelligence in personalized engagement marketing. California Management Review. 2019; 61(4): 135-55. https://doi.org/10.1177/0008125618959317
3. Gao Y, Liu H. Artificial intelligence-enabled personalization in interactive marketing: a customer journey perspective. Journal of Research in Interactive Marketing. 2023; 17(5): 663-80. https://doi.org/10.1108/JRIM-01-2022-0023
4. Oldemeyer L, Jede A, Teuteberg F. Investigation of artificial intelligence in SMEs: a systematic review of the state of the art and the main implementation challenges. Management Review Quarterly. 2025; 75(2): 1185-227. https://doi.org/10.1007/s11301-024-00405-4
5. Schwaeke J, et al. The new normal: The status quo of AI adoption in SMEs. Journal of Small Business Management. 2025; 63(3): 1297-331. https://doi.org/10.1080/00472778.2024.2379999
6. Dora M, et al. Critical success factors influencing artificial intelligence adoption in food supply chains. International Journal of Production Research. 2022; 60(14): 4621-40. https://doi.org/10.1080/00207543.2021.1959665
7. Solaimani S, et al. Exploration and prioritisation of critical success factors in adoption of artificial intelligence: a mixed-methods study. International Journal of Business Information Systems. 2024; 45(4):

429-53. https://doi.org/10.1504/IJBIS.2024.138052
8. Ta VA, Lin CY. Exploring the determinants of digital transformation adoption for SMEs in an emerging economy. Sustainability. 2023; 15(9): 7093. https://doi.org/10.3390/su15097093
9. Chuc ND, Anh DT. Digital transformation in Vietnam. Journal of Southeast Asian Economies. 2023; 40(1): 127-44. https://doi.org/10.1355/ae40-1f
10. Haleem A, et al. Artificial intelligence (AI) applications for marketing: A literature-based study. International Journal of Intelligent Networks. 2022; 3: 119-32. https://doi.org/10.1016/j.ijin.2022.08.005
11. Grewal D, et al. How generative AI is shaping the future of marketing. Journal of the Academy of Marketing Science. 2025; 53(3): 702-22. https://doi.org/10.1007/s11747-024-01064-3
12. Huang MH, Rust RT. A strategic framework for artificial intelligence in marketing. Journal of the Academy of Marketing Science. 2021; 49(1): 30-50. https://doi.org/10.1007/s11747-020-00749-9
13. Jöhnk J, Weißert M, Wyrtki K. Ready or not, AI comes: an interview study of organizational AI readiness factors. Business and Information Systems Engineering. 2021; 63(1): 5-20. https://doi.org/10.1007/s12599-020-00676-7
14. Horani OM, et al. The critical determinants impacting artificial intelligence adoption at the organizational level. Information Development. 2025; 41(3): 1055-79.
15. Khanfar AA, et al. Factors influencing the adoption of artificial intelligence systems: a systematic literature review. Management Decision. 2025; 63(10): 3727-55. https://doi.org/10.1108/MD-05-2023-0838
16. Tornatzky LG, Fleischer M. The processes of technological innovation. Lexington (MA): Lexington Books; 1990.
17. Jonathan GM, et al. AI adoption in the public sector: Organizational readiness and the pursuit of public value. Complex Systems Informatics and Modeling Quarterly. 2025; (45): 43-70. https://doi.org/10.7250/csimq.2025-45.03
18. Solaimani S, Swaak L. Critical success factors in a multi-stage adoption of artificial intelligence: a necessary condition analysis. Journal of Engineering and Technology Management. 2023; 69: 101760. https://doi.org/10.1016/j.jengtecman.2023.101760
19. Babashahi L, et al. AI in the workplace: A systematic review of skill transformation in the industry. Administrative Sciences. 2024; 14(6): 127. https://doi.org/10.3390/admsci14060127
20. Hong Y, et al. Statistical perspectives on reliability of artificial intelligence systems. Quality Engineering. 2023; 35(1): 56-78. https://doi.org/10.1080/08982112.2022.2089854
21. Suseno Y, et al. Beliefs, anxiety and change readiness for artificial intelligence adoption among human resource managers: the moderating role of high-performance work systems. In: Artificial Intelligence and International HRM. London: Routledge; 2023. p. 144-71.
22. Awad A. Artificial intelligence and marketing innovation: The mediating role of organizational culture. Innovative Marketing. 2024; 20(3): 170. http://dx.doi.org/10.21511/im.20(3).2024.14
23. Siddiqui H, Khan A, Shaikh S. Unveiling barriers and enablers: A study on AI adoption in business management. Journal of Social and Organizational Matters. 2025; 4(1): 193-209.
24. Wang S, et al. The effects of government support on enterprises' digital transformation: Evidence from China. Managerial and Decision Economics. 2023; 44(5): 2520-39. https://doi.org/10.1002/mde.3831
25. Fernandes KJ, Milewski S, Chaudhuri A, Xiong Y. Contextualising the role of external partnerships to innovate the core and enabling processes of an organisation: A resource and knowledge-based view. Journal of Business Research. 2022; 144: 146-62. https://doi.org/10.1016/j.jbusres.2022.01.091
26. Linstone HA, Turoff M. The Delphi method: Techniques and applications. Reading (MA): Addison-Wesley; 2002.
27. Hsu CC, Sandford BA. The Delphi technique: Making sense of consensus. Practical Assessment, Research & Evaluation. 2007; 12(10): 1-8. https://doi.org/10.7275/pdz9-th90
28. Okoli C, Pawlowski SD. The Delphi method as a research tool: An example, design considerations and applications. Information

& Management. 2004; 42(1): 15-29. https://doi.org/10.1016/j.im.2003.11.002
29. Habibi A, Sarafrazi A, Izadyar S. Delphi technique theoretical framework in qualitative research. International Journal of Engineering Science. 2014; 3(4): 8-13.
30. Lawshe CH. A quantitative approach to content validity. Personnel Psychology. 1975; 28: 563-575.
31. Saaty TL. Decision making: The analytic hierarchy and network processes (AHP/ANP). Journal of Systems Science and Systems Engineering. 2004; 13(1): 1-35. https://doi.org/10.1007/s11518-006-0151-5
32. Chang DY. Applications of the extent analysis method on fuzzy AHP. European Journal of Operational Research. 1996; 95(3): 649-655. https://doi.org/10.1016/0377-2217(95)00300-2
33. Zadeh LA. Fuzzy sets. Information and Control. 1965; 8(3): 338-353. https://doi.org/10.1016/S0019-9958(65)90241-X
34. Patil SK, Kant R. A fuzzy AHP-TOPSIS framework for ranking the solutions of knowledge management adoption in supply chain. Expert Systems with Applications. 2014; 41(2): 679-693. https://doi.org/10.1016/j.eswa.2013.07.093
35. Kahraman C, Cebeci U, Ruan D. Multi-attribute comparison of catering service companies using fuzzy AHP: The case of Turkey. International Journal of Production Economics. 2004; 87(2): 171-184. https://doi.org/10.1016/S0925-5273(03)00099-9
36. Sayyadi M. How to improve data quality to empower business decision-making process and business strategy agility in the AI age. Business Information Review. 2024; 41(3): 124-129.
37. Faiz F, Le V, Masli EK. Determinants of digital technology adoption in innovative SMEs. Journal of Innovation & Knowledge. 2024; 9(4): 100610. https://doi.org/10.1016/j.jik.2024.100610
38. Morandini S, et al. The impact of artificial intelligence on workers' skills: Upskilling and reskilling in organisations. Informing Science. 2023; 26: 39-68. https://dx.doi.org/10.28945/5078
39. Dey PK, et al. Artificial intelligence-driven supply chain resilience in Vietnamese manufacturing small-and medium-sized enterprises. International Journal of Production Research. 2024; 62(15): 5417-5456. https://doi.org/10.1080/00207543.2023.2179859
40. Teece DJ. Explicating dynamic capabilities: The nature and microfoundations of (sustainable) enterprise performance. Strategic Management Journal. 2007; 28(13): 1319-1350. https://doi.org/10.1002/smj.640

How to cite this article: Nguyen Thi Thai Ha. Prioritizing critical success factors for artificial intelligence (AI) adoption in marketing among small and medium sized enterprises in Vietnam. *International Journal of Research and Review*. 2026; 13(6): 439-455.
DOI: *https://doi.org/10.52403/ijrr.20260644*

******