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Evaluation of the Effectiveness of Marketing Strategies of Small and Medium-Sized Enterprises (SMEs) under Uncertainty Using a Fuzzy Approach

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A B S T R A C T

In today's unstable and high-risk environments, small and medium-sized service enterprises (SMEs) increasingly face challenges in formulating and implementing marketing strategies. The present study aims to evaluate the effectiveness of marketing strategies under conditions of uncertainty by employing a fuzzy multi-criteria decision-making approach, designing a precise, data-driven model to enhance decision-making in such organizations. In terms of purpose, this study is applied in nature, and from a methodological perspective, it is descriptive–analytical, utilizing a pairwise comparison questionnaire to collect field data. The data were gathered through the participation of 13 experts, including senior managers and marketing and strategy specialists from service-oriented SMEs. For deriving the results, mathematical modeling based on fuzzy logic and multi-criteria decision-making (MCDM) methods was employed to assign more accurate weights to the criteria under uncertainty. The findings indicate that the proposed model demonstrates high capability in ranking marketing strategies and prioritizing key success factors, serving as a practical tool for managers in designing adaptive and flexible marketing programs. By integrating analytical and field approaches, this research offers a reliable framework for strategic decision-making in the dynamic service market environment.

Keywords: *Marketing strategies, Uncertainty conditions, Small and medium-sized enterprises (SMEs), Fuzzy approach*

1. Introduction

In the contemporary business environment, the rapid evolution of digital technologies has transformed how companies design, implement, and evaluate their marketing strategies. Digital marketing has shifted from being a complementary promotional tool to a core strategic component for organizations across sectors, driven by changing consumer behavior, technological advancements, and increased competition (Otto, 2024; Williams & Green, 2022). This paradigm shift is particularly relevant for small and medium-sized enterprises (SMEs), which often operate under constraints of resources and capabilities yet must compete in dynamic markets where agility, innovation, and effective consumer engagement are decisive factors (Deku et al., 2024; Otopah et al., 2024). The ability of SMEs to design effective digital marketing strategies that foster trust, enhance consumer engagement, and convert intentions into purchase behaviors has become a critical determinant of competitive advantage (Alizadeh et al., 2024; Zhang, 2024).

Digital marketing's effectiveness depends on the extent to which organizations can align technological capabilities with customer-centric approaches. Research emphasizes that consumer engagement—defined as the depth of cognitive, emotional, and behavioral investment in brand interactions—is a crucial driver of online purchasing, especially for new brands and digital-first businesses (Jackson & Brown, 2022; Zhang, 2024). In highly competitive and digitalized marketplaces, trust serves as both a prerequisite and an outcome of effective marketing strategies (Otopah et al., 2024; Zhang & Lee, 2023). Without sufficient trust, even sophisticated campaigns fail to translate into measurable business performance (Otto, 2024; Williams & Green, 2022). Furthermore, the rise of artificial intelligence (AI) in marketing has enabled hyper-personalized content delivery and real-time engagement monitoring, allowing companies to develop more precise and impactful strategies (Alizadeh & Foroughi, 2023; Andersson et al., 2024).

From a strategic perspective, SMEs must consider digital marketing as part of a broader strategic management process that includes strategic thinking, planning, and foresight (Ahi et al., 2022; Jahangiri et al., 2020). Strategic thinking allows organizations to anticipate future market shifts and technological disruptions, while strategic planning operationalizes these insights into actionable initiatives. Strategic foresight, in particular, enables SMEs to mitigate uncertainties and adapt to emerging challenges, ensuring that marketing strategies remain relevant in rapidly changing environments (Asgari et al., 2024; Zhou et al., 2021). The integration of digital marketing into the overall business strategy also requires consideration of competitive positioning, customer segmentation, and brand differentiation, which are increasingly dependent on technology-driven customer insights (Andersson et al., 2024; Lee & Chen, 2023).

The role of pricing strategies within digital marketing is another critical factor influencing consumer purchase intentions. Dynamic and value-based pricing, supported by data analytics, enables firms to respond quickly to market changes, competitor actions, and customer preferences (Feng & Chan, 2022; Hallberg, 2023). In addition, innovations in payment systems and omnichannel retailing have expanded consumer choices, increasing the importance of seamless, trust-enhancing digital experiences (García, 2021; Kim & Park, 2022). Studies have shown that co-creation with customers, especially in product innovation processes, strengthens the perceived value and differentiation of offerings, thereby reinforcing purchase intentions (García, 2021; Yang & Jiang, 2023). For SMEs, this collaborative approach can be a cost-effective strategy to enhance both innovation output and customer loyalty.

The link between innovation and marketing performance has been extensively documented, with open innovation practices enabling firms to access external knowledge and technologies, thus accelerating product development and market responsiveness (Kim & Park, 2022; Yang & Jiang, 2023). In SMEs, resource limitations often necessitate leveraging external networks, digital platforms, and strategic partnerships to overcome capability gaps (Asgari et al., 2024; Baykaso˘glu et al., 2020). Moreover, the alignment of green innovation with marketing strategies has emerged as a competitive necessity, reflecting growing consumer awareness of environmental sustainability (Yang & Jiang, 2023; Zhou et al., 2021). This alignment not only enhances corporate reputation but also opens opportunities in niche markets where environmental legitimacy is valued.

Despite the strategic importance of digital marketing, its implementation is not without challenges. One key obstacle is managing the complexity of the digital B2B and B2C customer journeys, where multiple touchpoints must be integrated into a coherent and personalized experience (Andersson et al., 2024; Lee & Chen, 2023). SMEs often face difficulties in acquiring and analyzing large volumes of customer data, which are necessary for refining targeting, messaging, and engagement strategies (Alizadeh et al., 2024; Otto, 2024). Furthermore, the speed of technological change means that tools and platforms used today may become obsolete in the near future, underscoring the importance of continuous capability development (Ahi et al., 2022; Jahangiri et al., 2020).

In addition, cultural and behavioral differences across markets affect the transferability of digital marketing practices (Deku et al., 2024; Otopah et al., 2024). For example, factors influencing consumer trust and engagement in banking services may differ significantly from those in retail or manufacturing (Otopah et al., 2024; Williams & Green, 2022). Similarly, while personalization and AI-driven recommendations may increase engagement in some markets, they may raise privacy concerns in others, thereby affecting perceived risk (Jackson & Brown, 2022; Zhang & Lee, 2023). Understanding these contextual factors is essential for SMEs aiming to expand beyond local markets and compete internationally.

The application of decision-making models, such as fuzzy multiple-attribute decision-making (FMADM), has gained attention as a means of systematically evaluating and prioritizing marketing strategies under uncertainty (Baykasoˇglu et al., 2020; Feng & Chan, 2022). Such models allow decision-makers to incorporate qualitative judgments and quantitative metrics, producing robust rankings of strategic options. For SMEs, this is particularly valuable in environments characterized by rapid technological disruption, shifting consumer demands, and high competitive intensity (Ahi et al., 2022; Asgari et al., 2024).

Ultimately, the effectiveness of digital marketing for SMEs depends on the integration of strategic planning, innovation, consumer trust-building, and data-driven decision-making (Alizadeh et al., 2024; Otto, 2024; Zhang, 2024). The interplay between these elements determines not only short-term sales performance but also long-term brand equity and market positioning (Kim & Park, 2022; Williams & Green, 2022). In this context, the present study seeks to contribute to the growing body of knowledge by developing a model for evaluating and prioritizing digital marketing strategies for SMEs operating under uncertainty, leveraging fuzzy decision-making techniques to ensure both analytical rigor and practical applicability (Asgari et al., 2024; Baykasoˇglu et al., 2020). This approach aims to provide actionable insights for SME managers, enabling them to allocate resources effectively, adapt to evolving market conditions, and sustain competitive advantage in the digital era.

2. Methods and Materials

This research is applied in terms of its objective and descriptive–analytical in terms of its nature and implementation method. Considering the nature of decision-making under uncertainty, a quantitative approach integrated with fuzzy logic was employed for data analysis. The primary aim of this study is to present a fuzzy logic-based decision-making model for evaluating and prioritizing marketing strategies in small and medium-sized service enterprises operating in dynamic and unstable environments.

The statistical population of this research consists of senior managers, strategy experts, and marketing officers active in small and medium-sized service enterprises (SMEs) in Tehran Province. The sampling method was non-probability purposive (judgmental) sampling, and 13 experts with a minimum of five years of managerial experience in related fields were selected as the sample.

Data were collected through two main methods:

a) **Library method**: The theoretical foundations and conceptual framework of the research were extracted from scientific sources, reputable domestic and international articles, specialized books, and dissertations.

b) **Field method**: To collect empirical data, a fuzzy pairwise comparison questionnaire was used. This questionnaire was designed based on a fuzzy linguistic scale (such as “much more important,” “slightly more important,” etc.) and was completed with the participation of the experts.

The fuzzy questionnaire used consisted of pairwise comparison matrices for evaluating the criteria and sub-criteria influencing the effectiveness of marketing strategies under uncertainty. Responses were obtained as linguistic variables and then converted into triangular fuzzy numbers.

For data analysis, a combination of fuzzy multi-criteria decision-making (Fuzzy MCDM) models was applied. The main steps of the analysis included:

- Identifying key decision-making criteria through literature review and expert opinions.
- Constructing the fuzzy pairwise comparison matrix to calculate the weights of the criteria (using Fuzzy AHP).
- Integrating the weights and evaluating the strategic options using the Fuzzy TOPSIS method to rank and select the optimal marketing strategy under uncertainty.
- Validating the final model through sensitivity analysis, consistency checks, and expert feedback.

The face and content validity of the questionnaire were examined and confirmed by a specialist panel consisting of five university professors and eight senior marketing managers.

The reliability of the instrument was assessed using the Consistency Ratio (CR) in the AHP method, which was found to be less than 0.1, indicating the desirable reliability of the data. In addition, to enhance confidence, the responses were re-analyzed using fuzzy averaging and group consistency testing.

3. Findings and Results

In the first stage of the research process, in order to identify the most accurate and context-specific indicators related to the effectiveness of marketing strategies under uncertainty, the opinions of experts in the fields of marketing and strategic management in small and medium-sized service enterprises (SMEs) located in Tehran Province were utilized. The selected experts had at least five years of executive experience at senior managerial levels and provided their perspectives through semi-structured interviews and open-ended questionnaires.

Table 1

Research Criteria and Sub-Criteria

Criterion	Criterion Code	Sub-Criterion	Sub-Criterion Code
Marketing	C1	Target market	S11
		Market competition	S12
		Demand elasticity	S13
Innovation	C2	Degree of innovation	S21
		Product development capability	S22
		New product life cycle	S23
Organization	C3	Structure	S31
		Culture	S32
		Participation	S33
Customer	C4	Willingness to pay	S41
		Customization for customers	S42
		Product segmentation for different customer groups	S43
		Customer complexity	S44
		Purchase frequency	S45
Technology	C5	Payment channels	S51
		Security infrastructure	S52
		Consumer search capability	S53
		Unique technology	S54
Product	C6	Product type convenience	S61
		After-sales support	S62
		Brand	S63
		Delivery	S64

The next step in the research process was to analyze the internal relationships among the identified indicators. For this purpose, the final interrelationship matrix among the main criteria (W22) was calculated using the fuzzy Decision-Making Trial and Evaluation Laboratory (Fuzzy DEMATEL) technique. This technique is one of the advanced structural analysis methods that allows the identification of causal relationships between criteria while simultaneously showing the degree of influence and dependence of each variable.

The application of the fuzzy DEMATEL method in this study enables researchers to incorporate the uncertainties and ambiguities inherent in expert judgments, thereby producing a more accurate and realistic structure of the network of relationships among criteria. In this regard, a fuzzy linguistic variable scale was used to assess the intensity of the influence of each criterion on the others, as shown in Table 2.

Table 2

Fuzzy Scale and DEMATEL Technique

Linguistic Variable	Quantitative Equivalent	Fuzzy Quantitative Equivalent
		l
No influence	0	0.0
Low influence	1	0.1
Influential	2	0.3
High influence	3	0.5
Very high influence	4	0.7

In the group fuzzy DEMATEL technique, when the perspectives of several experts or specialists are used, simple arithmetic averaging is applied to aggregate the opinions and reach a shared result. In other words, to construct the direct-relation matrix (M), the individual judgment matrix of each expert was first defined as triangular fuzzy numbers (TFNs), and then, for each element, the fuzzy average of all experts' opinions was calculated.

In this study, the same procedure was followed: the data obtained from the fuzzy DEMATEL questionnaires—presented as fuzzy pairwise comparisons among the criteria—were fuzzified separately for each expert. Subsequently, by calculating the fuzzy average of corresponding elements in the individual matrices, the group fuzzy direct-relation matrix (Fuzzy Direct-Relation Matrix – M) was obtained as the initial input for the fuzzy DEMATEL process.

This matrix represents the magnitude of the direct influence of each criterion on other criteria in the fuzzy decision-making space and serves as the basis for converting into the normalized matrix, calculating the total relation matrix, and mapping the causal relationships in the subsequent stages of the analysis.

Table 3

Direct-Relation Matrix

	C1	C2	C3	C4	C5	C6
C1	0.300 0.730 0.500 0.820 0.970 0.770					
	0.100 0.540 0.300 0.620 0.840 0.580					
	0.000 0.370 0.150 0.430 0.640 0.380					
C2	0.600 0.300 0.680 0.550 0.990 0.760					
	0.400 0.100 0.480 0.380 0.880 0.560					
	0.240 0.000 0.290 0.220 0.680 0.370					
C3	0.480 0.650 0.300 0.780 1.000 0.720					
	0.450 0.480 0.100 0.520 0.720 0.520					
	0.300 0.320 0.000 0.330 0.520 0.340					
C4	0.650 0.470 0.540 0.300 0.770 0.760					
	0.460 0.280 0.340 0.100 0.620 0.560					
	0.290 0.150 0.170 0.000 0.440 0.370					
C5	0.790 0.800 0.640 0.840 0.300 0.850					
	0.660 0.620 0.440 0.640 0.100 0.660					
	0.490 0.420 0.270 0.440 0.000 0.460					
C6	0.790 0.890 0.620 0.800 0.970 0.300					
	0.830 0.740 0.420 0.520 0.680 0.100					
	0.640 0.540 0.250 0.320 0.480 0.000					
Row sum	3.610 3.840 3.280 4.090 5.000 4.160					

To normalize the values, the sum of uiju_{ij}uij for each row must be calculated. By dividing the elements of the fuzzy matrix X~\tilde{X}X~ by the maximum value of ∑uij\sum u_{ij}∑uij, the normalized fuzzy matrix N~\tilde{N}N~ will be obtained, where the result is 0.200.

Table 4

Normalized Matrix (N) of the Main Criteria

N	C1	C2	C3	C4	C5	C6
C1	0.060 0.146 0.100 0.164 0.194 0.154					
	0.020 0.108 0.060 0.124 0.168 0.116					
	0.000 0.074 0.030 0.086 0.128 0.076					
C2	0.120 0.060 0.136 0.110 0.198 0.152					
	0.080 0.020 0.096 0.076 0.176 0.112					
	0.048 0.000 0.058 0.044 0.136 0.074					
C3	0.096 0.130 0.060 0.156 0.200 0.144					
	0.090 0.096 0.020 0.104 0.144 0.104					
	0.060 0.064 0.000 0.066 0.104 0.068					
C4	0.130 0.094 0.108 0.060 0.154 0.152					
	0.092 0.056 0.068 0.020 0.124 0.112					
	0.058 0.030 0.034 0.000 0.088 0.074					

C5	0.158 0.160 0.128 0.168 0.060 0.170
	0.132 0.124 0.088 0.128 0.020 0.132
	0.098 0.084 0.054 0.088 0.000 0.092
C6	0.158 0.178 0.124 0.160 0.194 0.060
	0.166 0.148 0.084 0.104 0.136 0.020
	0.128 0.108 0.050 0.064 0.096 0.000

To compute the total-relation matrix, the relation N×(I−N)−1N \times (I - N)^{-1}N×(I−N)−1 is used. In the fuzzy DEMATEL method, the normalized fuzzy matrix is decomposed into the following three crisp matrices:

Nu=[…uij…]N_u = [\dots u_{ij} \dots]Nu=[…uij…]

Nm=[…mij…]N_m = [\dots m_{ij} \dots]Nm=[…mij…]

Nl=[…lij…]N_l = [\dots l_{ij} \dots]Nl=[…lij…]

Then, the identity matrix In×nI_{n \times n}In×n is constructed and the following operations are performed:

Tl=Nl×(I−Nl)−1T_l = N_l \times (I - N_l)^{-1}Tl=Nl×(I−Nl)−1

Tm=Nm×(I−Nm)−1T_m = N_m \times (I - N_m)^{-1}Tm=Nm×(I−Nm)−1

Tu=Nu×(I−Nu)−1T_u = N_u \times (I - N_u)^{-1}Tu=Nu×(I−Nu)−1

t~ij=(tijl,tijm,tiju)\tilde{t}_{ij} = (t_{ij}^l , t_{ij}^m , t_{ij}^u)t~ij=(tijl,tijm,tiju)

Table 5

Total-Relation Matrix (T) of the Main Criteria

	C1	C2	C3	C4	C5	C6
C1	0.572 0.676 0.560 0.722 0.854 0.724					
	0.168 0.241 0.165 0.255 0.336 0.258					
	0.048 0.112 0.058 0.122 0.177 0.117					
C2	0.606 0.576 0.572 0.652 0.830 0.697					
	0.218 0.155 0.192 0.207 0.333 0.247					
	0.092 0.042 0.081 0.082 0.180 0.112					
C3	0.588 0.642 0.504 0.694 0.834 0.694					
	0.224 0.222 0.120 0.229 0.305 0.238					
	0.101 0.100 0.026 0.101 0.152 0.106					
C4	0.568 0.559 0.504 0.552 0.729 0.644					
	0.208 0.170 0.151 0.134 0.263 0.225					
	0.092 0.063 0.053 0.032 0.127 0.103					
C5	0.674 0.702 0.597 0.741 0.755 0.753					
	0.274 0.259 0.193 0.263 0.214 0.276					
	0.139 0.123 0.080 0.125 0.067 0.133					
C6	0.693 0.737 0.610 0.753 0.897 0.674					
	0.310 0.288 0.196 0.251 0.330 0.184					
	0.168 0.148 0.079 0.108 0.160 0.052					

For defuzzification of the direct-relation matrix, after calculating the row mean of the fuzzy values for each criterion, the crisp values of the total-relation matrix are obtained, as shown in Table 6.

Table 6

Total-Relation Matrix (T) of the Main Criteria – Defuzzified

T	C1	C2	C3	C4	C5	C6
C1	0.263 0.305 0.304 0.289 0.363 0.390					
C2	0.343 0.257 0.321 0.264 0.362 0.391					
C3	0.261 0.282 0.217 0.236 0.290 0.295					
C4	0.366 0.314 0.342 0.239 0.376 0.371					
C5	0.456 0.448 0.430 0.373 0.345 0.462					
C6	0.366 0.352 0.346 0.324 0.387 0.303					
Column sum	2.055 1.958 1.960 1.725 2.123 2.212					

	0.334

To determine the network relationship map (NRM), the threshold value must be calculated. After determining the threshold intensity, all values in the T matrix that are smaller than the threshold are set to zero, meaning that such a causal relationship is not considered. In this study, the threshold value was obtained as 0.334. Based on the relationship pattern, the causal diagram can be drawn.

Table 7

Significant Relationship Pattern of Sub-Criteria

T	C1	C2	C3	C4	C5	C6
C1	*	*	*	*	0.363	0.390
C2	0.343	*	*	*	0.362	0.391
C3	*	*	*	*	*	*
C4	0.366	*	0.342	*	0.376	0.371
C5	0.456	0.448	0.430	0.373	*	0.462
C6	0.366	*	0.346	*	0.387	*

Table 8

Causal Relationship Pattern of Study Indicators

	D	R	D+R	D–R
C1	1.915	2.055	3.970	–0.141
C2	1.939	1.958	3.896	–0.019
C3	1.580	1.960	3.540	–0.380
C4	2.008	1.725	3.734	0.283
C5	2.514	2.123	4.636	0.391
C6	2.079	2.212	4.291	–0.134

In Table 8, the output of the fuzzy DEMATEL analysis is presented as decision vectors, including D (row sum) and R (column sum). The sum of the elements in each row (D) indicates the degree of direct influence of each factor on other factors in the system. Accordingly, the “Technology” criterion has the highest degree of influence among all other criteria and is recognized as the most influential element in the internal relationship network.

In contrast, the sum of the elements in each column (R) for each factor indicates the degree to which that factor is influenced by other factors in the system. The results show that the “Product” criterion has the highest degree of being influenced, meaning that changes in other factors can have the greatest effect on it.

On the other hand, the algebraic sum of these two vectors (D + R), known as the system interaction vector, specifies the level of interaction and overall connection of each factor with the other factors. In fact, the greater the value of (D + R) for a factor, the more central its position in systemic interactions. According to the results, the “Technology” criterion has the highest level of overall interaction in the system and plays a central role.

The other vector, (D – R), represents the difference between the influence and the being influenced of each factor. A positive value in this vector means that influence outweighs being influenced, and such a variable is referred to as a causal variable. Conversely, a negative value indicates the effect-receiving nature of the factor.

Based on the calculations, the “Technology,” “Customer,” and “Product” criteria have positive (D – R) values and thus fall into the category of causal variables (system drivers). In contrast, the “Marketing,” “Innovation,” and “Organization” criteria have negative values in (D – R) and are recognized as effect variables (effect receivers). This classification is highly important for designing strategic interventions and focusing resources on driving factors.

In this study, the Analytic Network Process (ANP) technique was used to determine the weights of the model criteria.

To conduct the network analysis, the main criteria were compared pairwise based on the objective. Pairwise comparison is very simple, and all elements of each cluster must be compared two by two. Therefore, if there are *n* elements in a cluster, $(n(n-1))/2$ comparisons will be made.

The experts' opinions were quantified using a fuzzy scale. Initially, expert opinions were collected using a nine-degree Saaty scale. Then, the expert opinions were fuzzified. To aggregate expert opinions in the fuzzy ANP method, the geometric mean approach was used. Based on the results obtained from aggregating expert opinions, the pairwise comparison matrix is presented in Table 9.

Table 9

Pairwise Comparison Matrix of Components

	C1	C2	C3	C4	C5	C6
C1	1.000 0.748 0.470 0.455 0.555 0.576					
	1.000 0.576 0.375 0.376 0.455 0.454					
	1.000 0.462 0.319 0.324 0.441 0.386					
C2	2.166 1.000 0.870 0.877 1.148 1.730					
	1.736 1.000 0.713 0.729 0.890 1.379					
	1.337 1.000 0.591 0.610 0.696 1.091					
C3	3.132 1.692 1.000 1.717 0.933 1.196					
	2.664 1.403 1.000 1.355 0.741 0.964					
	2.130 1.149 1.000 1.041 0.595 0.794					
C4	3.084 1.638 0.960 1.000 1.808 1.297					
	2.663 1.371 0.738 1.000 1.446 1.064					
	2.199 1.140 0.582 1.000 1.208 0.882					
C5	2.267 1.437 1.681 0.828 1.000 1.446					
	2.200 1.124 1.350 0.691 1.000 1.125					
	1.801 0.871 1.072 0.553 1.000 0.886					
C6	2.593 0.916 1.259 1.134 1.129 1.000					
	2.203 0.725 1.037 0.940 0.889 1.000					
	1.738 0.578 0.836 0.771 0.692 1.000					

After forming the resulting pairwise comparison matrix, the fuzzy sum of each row is calculated. Then, to normalize the preferences of each criterion, the sum of the values of that criterion must be divided by the sum of all preferences (column elements). Since the values are fuzzy, the fuzzy sum of each row is multiplied by the inverse of the sum. Each obtained value represents the fuzzy and normalized weight corresponding to the main criteria. In the final step, the values are defuzzified and crisp numerical calculations are carried out. The calculations for determining the priority of the main criteria are as follows:

Table 10

Defuzzification of Normalized Weights of Study Components

	X1max	X2max	X3max	Deffuzy	Normal
C1	0.315	0.313	0.312	0.315	0.303
C2	0.161	0.159	0.157	0.161	0.155
C3	0.135	0.134	0.132	0.135	0.130
C4	0.131	0.130	0.129	0.131	0.126
C5	0.142	0.140	0.138	0.142	0.136
C6	0.156	0.154	0.152	0.156	0.150

Based on the obtained eigenvector:

Strategic marketing, with a normalized weight of 0.303, has the highest priority.

Innovation, with a normalized weight of 0.155, ranks second.

Product, with a normalized weight of 0.150, ranks third.

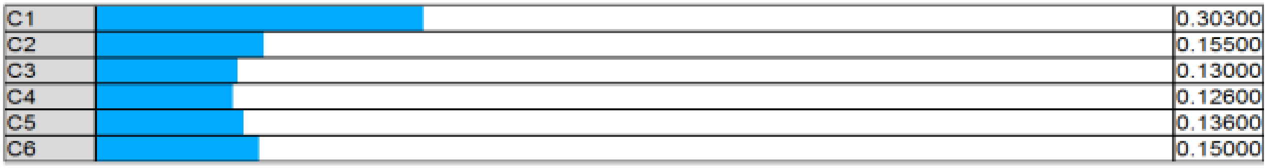
Technology, with a normalized weight of 0.136, ranks fourth.

Organization, with a normalized weight of 0.130, ranks fifth.

Customer, with a normalized weight of 0.126, has the lowest priority.

Figure 1

Graphical Representation of the Priority of Research Components

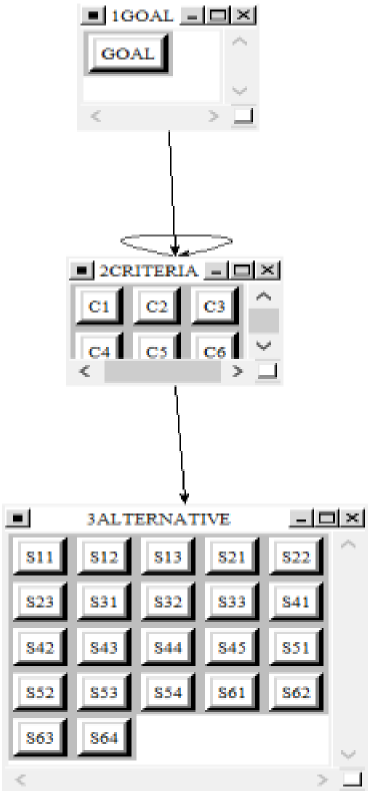


The inconsistency rate of the pairwise comparisons was calculated as 0.015, which is less than 0.1; therefore, the comparisons can be considered reliable.

To determine the final weight, the output of the comparison of the main criteria—based on the objective and the internal relationships among the criteria—is presented in a supermatrix. This supermatrix is referred to as the initial or unweighted supermatrix. To obtain the final priority in systems with mutual influences, the vectors of internal priorities (i.e., the calculated *w* values) are placed into the appropriate columns of a matrix. As a result, a supermatrix (essentially a partitioned matrix) is obtained, where each section of the matrix represents the relationship between two clusters in the system (Zabardast, 2010). The network model pattern was designed using the Analytic Network Process (ANP) technique in the Super Decisions software. Based on this model, the network analysis process diagram (ANP) is shown in Figure 2.

Figure 2

ANP Diagram of Index Priorities in Super Decisions Software



Based on the calculations performed in steps one to four, the unweighted (initial) supermatrix was obtained. In the next step, using the concept of normalization, the unweighted supermatrix was converted into a weighted (normalized) supermatrix. In the weighted supermatrix, the sum of the elements in each column is equal to one. The next step was to calculate the limit supermatrix. The limit supermatrix is obtained by raising all the elements of the weighted supermatrix to a sufficiently large power. This process is repeated until all the elements in the supermatrix become identical. In this case, all the entries of the supermatrix become zero, and only the entries related to the sub-criteria take on a numerical value that is repeated in all the rows corresponding to that entry.

Therefore, the final priority of the criteria is presented in Table 11.

Table 11

Final Weight of Indicators Based on the Limit Supermatrix

Criterion	Sub-Criterion	Final Weight	Ranking
Marketing	Target market	0.069	4
	Market competition	0.059	5
	Demand elasticity	0.038	17
Innovation	Degree of innovation	0.073	3
	Product development capability	0.073	2
	New product life cycle	0.020	22
Organization	Structure	0.040	11
	Culture	0.086	1
	Participation	0.039	14
Customer	Willingness to pay	0.046	8
	Customization for customers	0.040	12
	Product segmentation for different customer groups	0.025	20
	Customer complexity	0.023	21
	Purchase frequency	0.031	18
Technology	Payment channels	0.048	7
	Security infrastructure	0.038	16
	Consumer search capability	0.039	15
	Unique technology	0.045	9
Product	Product type convenience	0.030	19
	After-sales support	0.040	10
	Brand	0.040	13
	Delivery	0.058	6

Based on the calculations and using the limit supermatrix in the Super Decisions software, the final priority of the criteria and sub-criteria of the research model was determined. At this stage, considering the mutual influences among the indicators, the final weight of each sub-criterion was calculated using the Fuzzy Analytic Network Process (FANP) technique.

The results indicate that considering the internal relationships between the model variables changes the importance level and ranking of the sub-criteria. Unlike linear hierarchical methods that ignore dependencies among criteria, the FANP approach incorporates these interactions, offering a more realistic representation of the dynamics of organizational decision-making.

According to the FANP output, "organizational culture" with a final weight of 0.086 ranks first and is identified as the most important sub-criterion influencing the research model. "Product development capability" with a weight of 0.073 ranks second, and "degree of innovation," also with a weight of 0.073, ranks third. These results indicate that soft organizational dimensions and innovation-related factors play a critical role in strategic marketing under uncertainty and should receive particular attention in strategy formulation.

4. Discussion and Conclusion

The results of the present study, which aimed to evaluate and prioritize marketing strategies for small and medium-sized service enterprises (SMEs) operating under uncertainty using a fuzzy multi-criteria decision-making approach, provide important insights into the strategic priorities of firms in competitive and dynamic environments. The findings indicate that "strategic marketing" emerged as the most influential and highest-priority criterion, followed by "innovation" and "product." "Technology" ranked fourth, while "organization" and "customer" held the lowest priorities. In addition, the fuzzy DEMATEL analysis revealed that technology, customer, and product variables functioned as causal drivers within the network of internal relationships, exerting more influence than they received. Conversely, marketing, innovation, and organization were identified as effect variables, being more influenced by other factors than influencing them. This structural differentiation between causal and effect variables offers a nuanced understanding of where strategic interventions should be focused.

The prominence of strategic marketing as the highest-priority criterion is consistent with previous research emphasizing the centrality of coherent, targeted, and adaptive marketing efforts in enhancing SMEs' competitiveness in volatile environments (Otto, 2024; Williams & Green, 2022). Strategic marketing facilitates the alignment of market segmentation, value proposition, and brand positioning with evolving customer needs, enabling firms to maintain relevance and responsiveness (Alizadeh et al., 2024; Andersson et al., 2024). Moreover, digital marketing capabilities—integral to modern strategic marketing—are shown to significantly enhance purchase intention through mechanisms of engagement and trust (Otopah et al., 2024; Zhang, 2024), corroborating the emphasis on marketing as the central lever in the current findings.

Innovation's second-place ranking in the prioritization is also aligned with the literature, which repeatedly underscores the role of innovation, particularly open innovation, in enabling SMEs to respond quickly to market changes and technological disruptions (Kim & Park, 2022; Yang & Jiang, 2023). Innovation supports differentiation, which is essential for sustaining competitive advantage when competing with resource-rich larger firms (Asgari et al., 2024; García, 2021). The positive causal influence of product-related criteria further reinforces the argument that innovation is not an abstract organizational function but a concrete driver of market offerings, shaping both consumer perceptions and purchase behaviors (Hallberg, 2023; Zhang & Lee, 2023).

The identification of technology as a causal driver with the highest influence on other variables confirms the growing recognition of technology as both an enabler and a strategic asset (Ahi et al., 2022; Andersson et al., 2024). In the context of SMEs, technology enhances marketing reach, operational efficiency, and customer interaction quality (Lee & Chen, 2023; Otto, 2024). Advanced data analytics, artificial intelligence, and digital platforms facilitate more personalized and timely engagement, leading to stronger customer relationships and improved business performance (Alizadeh & Foroughi, 2023; Zhang, 2024). The fact that technology holds a pivotal causal position in the relationship network suggests that investments in technological infrastructure can yield spillover benefits for marketing, innovation, and customer-related performance metrics.

Interestingly, customer-related variables, despite being ranked lowest in priority in the overall weighting, were found to be causal drivers in the fuzzy DEMATEL analysis. This suggests that while customers may not be perceived as an immediate strategic priority compared to marketing or innovation, their complexity, segmentation, and purchasing behaviors significantly influence the effectiveness of other strategic areas (Jackson & Brown, 2022; Otopah et al., 2024). This paradox can be interpreted in light of research showing that trust and engagement—critical elements of customer relationships—mediate the impact of marketing strategies on purchase intentions (Otto, 2024; Williams & Green, 2022). Thus, even if customers are ranked lower in direct priority, their role as a causal factor in the system indicates a need for more nuanced customer-centric strategies.

The product criterion's causal influence aligns with empirical evidence that product quality, innovation, and post-sales support play a decisive role in determining purchase decisions (García, 2021; Kim & Park, 2022). In competitive markets, products that integrate innovative features, high reliability, and relevant branding outperform those relying solely on promotional efforts (Baykasoˇglu et al., 2020; Hallberg, 2023). Moreover, consumer co-creation in product development, as highlighted in previous research, increases the perceived value and strengthens the relationship between the firm and its customers (García, 2021; Yang & Jiang, 2023). The current findings reinforce the view that product strategy must be considered not just as a functional aspect of operations but as a driver of broader marketing effectiveness.

Conversely, the classification of marketing, innovation, and organization as effect variables suggests that these areas are more reactive to changes in other domains, particularly technology and product development. This is consistent with studies indicating that marketing strategies in SMEs often depend heavily on available technological capabilities, product portfolios, and the structure of customer relationships (Alizadeh et al., 2024; Andersson et al., 2024). Organizational structure and culture, while important for long-term adaptability, may not exert strong causal influence in the short term (Asgari et al., 2024; Jahangiri et al., 2020). Instead, they serve as enabling environments in which more directly impactful variables—technology, product, and customer engagement—can operate effectively.

The application of fuzzy multi-criteria decision-making in this study provided a robust analytical framework for capturing both qualitative judgments and quantitative assessments, enabling a more accurate prioritization under uncertainty (Baykasoˇglu et al., 2020; Feng & Chan, 2022). This methodological approach aligns with calls in the literature for decision-support tools that can accommodate the ambiguity inherent in expert evaluations, especially in dynamic markets (Ahi et al., 2022; Yang & Jiang, 2023). The integration of fuzzy DEMATEL and ANP not only allowed the identification of causal and effect variables but also provided a precise ranking of strategic priorities, offering actionable guidance for managers.

A noteworthy implication of the findings is that SMEs should focus their limited resources on strengthening causal variables—particularly technology, product, and customer factors—as these have the potential to trigger positive changes across the entire strategic system (Otto, 2024; Zhang, 2024). Marketing and innovation, while important, may achieve greater impact when supported by strong technological foundations and customer-driven insights. This is consistent with research indicating that the integration of technology into customer relationship management and product innovation amplifies the overall effectiveness of marketing strategies (Alizadeh & Foroughi, 2023; Lee & Chen, 2023).

In sum, the study's results resonate with and extend prior literature on digital marketing, innovation, and strategic management in SMEs. The identification of causal and effect variables provides a system-level perspective on strategic priorities, moving beyond isolated factor analysis toward a holistic understanding of interdependencies (Andersson et al., 2024; Williams & Green, 2022). By applying fuzzy decision-making techniques, this research bridges the gap between theory and practice, offering a decision-support framework that can be adapted to other contexts facing uncertainty and complexity.

While the study provides valuable insights, several limitations should be noted. First, the sample size was limited to a relatively small group of experts from SMEs in a specific geographic region, which may affect the generalizability of the results to other sectors or regions. Second, the reliance on expert judgments, while suitable for fuzzy multi-criteria analysis, introduces the potential for subjective bias, especially in prioritizing criteria. Third, the study's cross-sectional design limits its ability to capture changes in strategic priorities over time, particularly in rapidly evolving technological and market contexts. Finally, although the integration of fuzzy DEMATEL and ANP offers robust analytical capabilities, the complexity of the methodology may pose challenges for replication by practitioners without specialized knowledge.

Future research could expand the scope by including a larger and more diverse set of SMEs across different industries and geographic regions to enhance external validity. Longitudinal studies would be valuable in examining how strategic priorities shift over time, especially in response to technological disruptions or macroeconomic changes. Comparative studies between SMEs and large enterprises could also reveal differences in strategic emphasis and resource allocation. Additionally, integrating customer survey data alongside expert evaluations could provide a more comprehensive understanding of how end-user perceptions align with managerial priorities. Finally, testing the proposed decision-making framework in experimental or real-world strategic planning scenarios could help validate its practical applicability and refine its components.

Practitioners should focus on strengthening causal variables such as technology, product development, and customer engagement, as improvements in these areas are likely to yield broad systemic benefits. Investments in digital infrastructure and data analytics capabilities can enhance both marketing and innovation outcomes. Managers should also adopt a more integrated approach to strategy, ensuring that marketing and innovation activities are directly informed by technological capabilities and customer insights. Regular reassessment of strategic priorities using tools like fuzzy MCDM can help organizations remain agile and responsive in uncertain environments. Finally, fostering cross-functional collaboration between marketing, R&D, and IT teams can maximize the synergies among the most influential strategic areas.

Authors' Contributions

Authors contributed equally to this article.

Declaration

In order to correct and improve the academic writing of our paper, we have used the language model ChatGPT.

Transparency Statement

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References

Ahi, F., Toulabi, Z., & Mohammadi, A. (2022). The effect of strategic thinking and strategic planning on the performance of the company with the moderating role of strategic foresight (case study: Gas Company of Kermanshah Province). *Scientific Journal of New Research Approaches in Management and Accounting*, *5*(17), 10-22. https://majournal.ir/index.php/ma/article/view/907

Alizadeh, H., & Foroughi, M. (2023). A Strategic SWOT Analysis of Leading Electronics Companies based on Artificial intelligence. *International Journal of Business Management and Entrepreneurship (IJBME)*, *2*(2), 1-16. https://doi.org/10.1109/ICDCECE57866.2023.10150589

Alizadeh, H., Khorramabadi, M., Saberian, H., & Keramati, M. (2024). Qualitative Study to Propose Digital Marketing based on Customer experience: Considering Grounded theory (GT). *Business, Marketing, and Finance Open*, *1*(6), 86-98. https://doi.org/10.61838/bmfopen.1.6.8

Andersson, S., Aagerup, U., Svensson, L., & Eriksson, S. (2024). Challenges and opportunities in the digitalization of the B2B customer journey. *Journal of Business & Industrial Marketing*, *39*(13), 160-174. https://doi.org/10.1108/JBIM-12-2023-0714

Asgari, N., Javashi Jadid, S., Ghorani, S. F., & Ghaed, K. (2024). Modeling the facilitating role of information technologies and technology-oriented social networks in the implementation of organizational knowledge management. *New Approaches in Management and Marketing*, *2*(2), 100-111. https://www.jnamm.ir/article_187298.html?lang=en

Baykasoˇglu, A., Gölcük, I., & Akyol, D. E. (2020). *A fuzzy multiple-attribute decision making model to evaluate new product pricing strategies*. Springer Science+Business Media New York.

Deku, W. A., Wang, J., & Preko, A. K. (2024). Digital marketing and small and medium-sized enterprises' business performance in emerging markets. *Asia Pacific Journal of Innovation and Entrepreneurship*, *18*(3), 251-269. https://doi.org/10.1108/APJIE-07-2022-0069

Feng, L., & Chan, Y. (2022). Joint pricing and production decisions for new products with learning curve effects under upstream and downstream trade credits. *European Journal of Operational Research*, *272*(3), 905-913. https://doi.org/10.1016/j.ejor.2018.07.003

García, R. (2021). The impact of co-creation with customers on product innovation in the home appliance industry. *Journal of Business Research*, *132*(5), 456-469.

Hallberg, N. L. (2023). The micro-foundations of pricing strategy in industrial markets: A case study in the European packaging industry. *Journal of Business Research*, *76*, 179-188. https://doi.org/10.1016/j.jbusres.2017.01.001

Jackson, R., & Brown, D. (2022). Consumer trust and engagement in digital marketing: Exploring the mediating role of perceived risk. *Journal of Digital Marketing*, *8*(4), 21-39.

Jahangiri, S., Farnia, M., & Thabeti Chobdar, L. (2020). How to use strategic planning in manufacturing companies and organizations. International Conference on Management, Tourism and Technology,

Kim, J., & Park, S. (2022). The role of open innovation in enhancing the performance of home appliance companies. *Technovation*, *114*, 102518.

Lee, Y., & Chen, T. (2023). Impact of digital marketing strategies on consumer purchase intentions for smart home appliances. *International journal of marketing studies*, *15*(3), 123-139.

Otopah, A. A., Dogbe, C. S. K., Amofah, O., & Ahlijah, B. (2024). Digital marketing and purchase intention of bank services: The role of trust and engagement. *International Journal of Bank Marketing*, *42*(7), 1920-1945. https://doi.org/10.1108/IJBM-02-2023-0097

Otto, P. (2024). The impact of digital marketing on consumer purchase intention through the mediating role of consumer engagement and the moderating role of trust. *Journal of Marketing Research*, *61*(1), 45-60.

Williams, P., & Green, T. (2022). Examining the impact of digital marketing strategies on purchase intentions: A case study of the automotive sector. *Journal of Marketing Development*, *19*(1), 58-75.

Yang, Y., & Jiang, Y. (2023). Does suppliers slack influence the relationship between buyers environmental orientation and green innovation? *Journal of Business Research*, *157*(1), 113569. https://doi.org/10.1016/j.jbusres.2022.113569

Zhang, X. (2024). Consumer engagement and trust in online purchasing of new brands: A digital content perspective. *Journal of Consumer Behavior*, *23*(1), 45-59.

Zhang, X., & Lee, M. (2023). The role of consumer trust in digital marketing effectiveness: An empirical study. *International Journal of Digital Marketing*, *7*(2), 92-108.

Zhou, K., Govindan, X., Xie, L., & Yan, L. (2021). How to drive green innovation in China's mining enterprises? Under the perspective of environmental legitimacy and green absorptive capacity. *Resources Policy*, *72*(1), 102038. https://doi.org/10.1016/j.resourpol.2021.102038