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Which Digital Marketing Strategy Works Best? A Sector-Based Fuzzy Decision Analysis

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ABSTRACT

Digital marketing strategy selection is a complex problem due to the diversity of available strategies and evaluation criteria. Businesses must determine which strategies are most effective while considering cost, brand impact, and customer engagement. However, the literature lacks sector-specific analyses and generally offers broad recommendations that ignore differences across industries. This study addresses this gap by developing a novel decision-making framework to identify the most suitable digital marketing strategies for the e-commerce, tourism, and healthcare sectors. The proposed model integrates the simple weight calculation (SIWEC) method for objective criteria weighting, the Interactive Reference Point approach for ranking alternatives, and Fermatean fuzzy numbers to better represent uncertainty. This combination enhances both analytical accuracy and decision flexibility. The findings indicate that programmatic and targeted digital advertising is the most effective strategy for e-commerce and healthcare, while artificial intelligence (AI)-powered personalized marketing is more suitable for tourism. The study also shows that priority criteria differ by sector. The main contributions include a sector-based evaluation framework and a hybrid fuzzy model with high explanatory power. The results suggest that businesses should adopt data-driven targeting in efficiency-oriented sectors and personalized approaches in experience-focused industries..

1. Introduction

Digital marketing refers to businesses using digital channels to market their products and services. Especially in a world of rapidly evolving technology, these practices help businesses operate at lower costs. Several digital marketing strategies are available for businesses to implement. Social media marketing is a channel that businesses pay significant attention to. Businesses can conduct paid activities on platforms like Instagram and TikTok. In addition, influencer marketing is very popular today [1]. In this process, products are promoted by well-known individuals on social media platforms. On the other hand, a significant number of businesses also use content marketing. In this

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context, information about products and services is provided through blogs, videos, or storytelling. Artificial intelligence (AI)-powered personalized marketing is also being considered by some companies today [2]. In this process, information about the profile of consumers using AI applications is obtained. Thanks to this information, products tailored to these individuals can be offered.

Determining effective digital marketing strategies is quite difficult for businesses. The main reason for this is the large number of strategies and the different criteria involved in choosing these strategies. For example, cost-effectiveness is considered a vital criterion in this process. The excessively high cost of the implemented strategy can put the business in a difficult financial position, jeopardizing the financial sustainability of operations. Furthermore, the contribution to brand image must be considered [3]. The strategy implemented in this process should support the perception of the brand as innovative and reliable. Otherwise, customers will not choose these products and services. On the other hand, the potential to build brand loyalty is another key criterion in this process. For some products, long-term customer loyalty needs to be established. Therefore, customer loyalty should be considered when developing digital marketing strategies for these products. The level of engagement can also play a significant role in the selection of these strategies [4]. For some products, businesses need to reach many customers. Therefore, attention should be paid to the level of engagement in digital marketing strategies for such products.

Businesses need to determine their priority digital marketing strategies. The large number of strategies and criteria makes this process quite complex. Businesses have different financial and operational capabilities. Therefore, they need to determine digital marketing strategies that suit their specific characteristics. Another important aspect of this process is the difficulty of implementing different digital marketing strategies simultaneously. Since each strategy creates new costs, implementing many strategies at once is not financially feasible for businesses [5]. Consequently, businesses need to identify and implement the strategy that best suits them. However, there is no consensus in the literature regarding which priority digital marketing strategies are appropriate for different types of businesses. This uncertainty can create several negative consequences for businesses. Businesses that implement the wrong strategy may experience financial setbacks. This situation jeopardizes the sustainability of digital marketing practices. In short, new studies are needed to determine the priority digital marketing strategies appropriate to the type of business.

The main objective of this study is to determine the most important digital marketing strategies for businesses. Within this framework, different decision-making models are created for the e-commerce, tourism, and healthcare sectors. The main motivation for this study is that digital marketing strategies will differ according to business types. Therefore, instead of a general analysis, a separate application was carried out for 3 different sectors. In this process, the weights of the criteria are calculated using the SIWEC technique. In addition, the Interactive Reference Point approach is taken into consideration in the ranking of strategies. On the other hand, Fermatean fuzzy numbers are integrated into the model. As a result, this study seeks to answer the following research questions: (1) What are the most suitable digital marketing strategies for the e-commerce, tourism and healthcare sectors? (2) What are the priority criteria that should be considered in determining effective digital marketing strategies?

The methodological contribution of this study does not arise from proposing each component as an entirely new technique, but from integrating three complementary analytical functions within a sector-specific decision framework. Fermatean fuzzy numbers provide a flexible representation of uncertainty by allowing a wider admissible space for membership and non-membership information. SIWEC transforms variation in expert evaluations into criteria weights, thereby reducing reliance on directly assigned subjective weights. IRPA subsequently evaluates the alternatives relative to reference points rather than relying solely on conventional ideal-solution distances. The integration therefore connects uncertainty representation, variation-sensitive criteria weighting, and reference-point-based alternative evaluation within a single analytical structure. More importantly, the same framework is applied separately to e-commerce, tourism, and healthcare, allowing both criteria importance and strategy rankings to vary across sectors rather than assuming a universal digital marketing decision structure. Accordingly, the methodological contribution should be understood as an integrated and sector-sensitive fuzzy MCDM architecture rather than as the introduction of three individually new techniques.

Purchase intention is one of the key criteria in increasing the effectiveness of digital marketing strategies. Purchase intention is the final stage before purchase, emerging when the consumer decides to allocate money for the product [6]. Therefore, consumers with high purchase intention have a higher conversion rate into actual buyers [7]. Theocharis [8] states that Generation Z is most influenced by the people they trust when purchasing technological products, and that digital marketing strategies should be tailored accordingly. Tiwari *et al.,* [9] also point out the importance of eWOM (electronic Word of Mouth) in digital marketing strategies, noting that consumer reviews also influence purchasing decisions. Furthermore, An and Ngo [10] conclude that personalized digital marketing strategies and engaging advertisements have a positive impact on consumer purchase intention. In addition, consumer trust is another important criterion in increasing the effectiveness of digital marketing strategies. Trust is a multi-dimensional concept that can be examined from psychological, sociological, and economic perspectives. From an economic perspective, trust is defined as the willingness of the trusting party to take a risk based on the expectation that the other party will perform a specific action [11]. In other words, trust represents a reciprocal relationship established between two parties [1]. While Jamil *et al.,* [12] emphasize in their research that firms should allocate more resources to building consumer trust in the field of digital marketing, Ahmad *et al.,* [13] find that consumer trust can be increased through well-planned digital marketing strategies and strategic decision-making processes. Mizukoshi [14] states that research on trust in social media should not be limited only to digital marketing and social media marketing but can also be linked to other research.

Another important criterion in increasing the effectiveness of digital marketing strategies is brand loyalty. Brand loyalty is defined as a consumer consistently and regularly shopping from a brand and exhibiting a positive attitude towards that brand [15]. Pereira *et al.,* [16] show that customer loyalty in the digital realm is increased by personalization, trust, loyalty programs, and social media. Uludag *et al.,* [5] demonstrate that digital marketing activities play a significant role in the formation of long-term brand loyalty by positively influencing consumer commitment. In addition, Amelia *et al.,* [17] state that digital marketing strategies are directly but only minimally affected by brand loyalty, and that effective digital marketing strategy, trust, and positioning are more decisive. Another important element in increasing the effectiveness of digital marketing strategies is brand image. Brand image refers to a series of associations and perceptions in the form of data, benefits, or attitudes that consumers know about the brand [18]. Habib *et al.,* [19] emphasizes that businesses should focus on strategies that increase consumer engagement and strengthen brand image, thereby achieving greater success in digital marketing activities. Oriakhi *et al.,* [2] stress the need for businesses to invest in digital marketing activities to improve their brand image and protect it from negative impacts. Alam and Al Mubarak [20] state that brand image and perception are important and that digital marketing strategies should be determined within this framework to positively change the perceptions of existing and potential customers. Tong *et al.,* [21] indicate that digital marketing effectiveness can be enhanced by recognizing brand image using computer vision algorithms based on deep learning.

User interaction level is another important criterion in increasing the effectiveness of digital marketing strategies. User interaction level refers to the behavioral, cognitive, and emotional interactions of users on social media, including active behaviors such as liking, sharing, and commenting [3]. Sanches and Ramos [22] emphasize the importance of social media interactions in digital marketing strategies and offer businesses an opportunity to improve by developing a new method. Imran *et al.,* [23] state that rates such as click-through and conversion provide insights into motivating stakeholders and developing targeted strategies in digital marketing. Elsayad [24] indicates that interaction indicators strengthen consumers' brand perception and purchase intention and have a positive impact on digital marketing strategies. Personalization is also an important criterion in increasing the effectiveness of digital marketing strategies. Personalization can be defined as the algorithmic matching of past behaviors or pre-programmed flows, disregarding user intent and mood [25]. Al-Ahmad *et al.,* [26] emphasize that businesses can achieve higher conversion and engagement rates when they tailor their digital marketing strategies to personalized preferences and behaviors. On the other hand, Neetika *et al.,* [27] state that personalization efforts using artificial intelligence in digital marketing strategies will improve consumer experiences. McKee *et al.,* [28] also indicate that personalized content in digital marketing, when used correctly and with high engagement, can improve the experience but may trigger privacy concerns.

Another important criterion in increasing the effectiveness of digital marketing strategies is sustainability. Indeed, digital marketing strategies play a significant role in ensuring sustainability [29]. In the context of digital transformation and increasing market competition, businesses must determine sustainable digital marketing strategies to ensure long-term growth. Sustainable marketing aims for marketing activities to be sustainable in environmental, social, and economic dimensions [30]. In addition, sustainability in the field of marketing is a multi-dimensional process that includes strategic planning, product development, pricing strategies, promotional activities, and distribution channels [31]. While Madhavi [32] emphasizes the importance of sustainability-oriented communication strategies in the field of digital marketing in her study, Wijaya *et al.,* [4] state that digital marketing plays a critical role in developing sustainability strategies. In addition, measurability is another important criterion in increasing the effectiveness of digital marketing strategies. The basic function of analytical tracking is; Digitalization enables businesses to better analyze consumers and make necessary adjustments to strengthen their position in the competitive global market [33]. Deák and Szabó [34] emphasize the impact of technological advancements and the increasing importance of data analytics in digital marketing. In contrast, Witarsyaha *et al.,* [35] argue that AI-based analytics systems, multi-device tracking, and privacy-focused regulations make it more difficult to evaluate the effectiveness of digital marketing.

The results of the literature review show that certain criteria are important in increasing the effectiveness of digital marketing strategies. These criteria are expressed in the study as purchase intention, consumer trust, brand loyalty, brand image, user engagement level, personalization, sustainability, and measurability. Since it is not possible to develop and improve all these criteria simultaneously, the aim is to identify the most important criterion. In this context, a new decision-making model is used to conduct the analysis in this study, aiming to fill the gaps in the relevant literature.

The selection of the sectors, criteria, and alternatives followed a relevance- and applicability-based screening process. E-commerce, tourism, and healthcare were selected because they represent distinct service and market contexts in which digital marketing plays an important role while customer interaction and decision-making characteristics differ substantially. This heterogeneity enables the framework to examine whether digital marketing priorities remain consistent across different sectoral settings rather than producing a single generalized recommendation. The criteria were identified from the digital marketing literature by focusing on factors that directly reflect consumer response, brand-related outcomes, implementation performance, and the long-term effectiveness of digital marketing activities. Factors that were highly sector-specific, conceptually overlapping with the selected criteria, or difficult to evaluate consistently across all three sectors were excluded. Accordingly, nine criteria were retained to provide a common evaluation structure applicable to each sector. Similarly, the six alternatives were selected because they represent widely applicable and distinguishable digital marketing strategy categories, covering social media, influencer-based, content-based, direct, targeted advertising, and AI-supported personalized approaches. More specialized tools or platform-specific practices were not treated as separate alternatives when they could be regarded as applications or subcategories of these broader strategies. This screening logic was used to maintain both comprehensiveness and comparability while avoiding unnecessary conceptual overlap among the criteria and alternatives.

2. Methodology

This part of this study is about the preliminaries of Fermatean fuzzy sets (FFSs) and formulations of SIWEC and IRPA, respectively. Fermatean fuzzy systems allow for the definition of a wider range of income deprivation with more flexible evaluation compared to Pythagorean or traditional fuzzy sets. In addition, while the weighting values of the criteria are obtained with SIWEC, alternatives are ranked with the help of IRPA. The methodology involved in these models is summarized in Figure 1.

2.1. FFSs

Consider that $\mathcal{S}$ is a universe of discourse. Then, an FFS $(\tilde{\tilde{\mathfrak{F}}})$ in $\mathcal{S}$ is described as in Equation (1) [36].

$$\tilde{\tilde{\mathfrak{F}}} = \left\{ \langle \mathscr{f}, \mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}), \mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}) \rangle | \mathscr{f} \in \mathcal{S} \right\} \tag{1}$$

Wherein $\mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}): \mathcal{S} \to [0,1]$ and $\mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}): \mathcal{S} \to [0,1]$ indicate the grades of membership and non-membership of $\mathscr{f} \in \mathcal{S}$ to the $\tilde{\tilde{\mathfrak{F}}}$, respectively. These grades satisfy the condition in Equation (2) for $\forall \mathscr{f} \in \mathcal{S}$.

$$0 \leq \left(\mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}) \right)^3 + \left(\mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}) \right)^3 \leq 1 \tag{2}$$

The grades of indeterminacy of $\mathscr{f}$ to $\tilde{\tilde{\mathfrak{F}}}$ is identified for $\tilde{\tilde{\mathfrak{F}}}$ and $\mathscr{f} \in \mathcal{S}$ with the help of Equation (3).

$$\pi_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}) = \sqrt[3]{1 - \left(\mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}) \right)^3 - \left(\mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}}(\mathscr{f}) \right)^3} \tag{3}$$

Suppose that $\tilde{\tilde{\mathfrak{F}}} = \left(\mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}}, \mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}} \right)$ is an FFN. Then, the score and accuracy functions of $\tilde{\tilde{\mathfrak{F}}}$ are expressed using Equations (4) and (5), respectively.

$$\mathbb{S}(\tilde{\tilde{\mathfrak{F}}}) = \frac{1 + \left(\mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}} \right)^3 - \left(\mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}} \right)^3}{2} \tag{4}$$

$$\hbar(\tilde{\tilde{\mathfrak{F}}}) = \left(\mathscr{s}_{\tilde{\tilde{\mathfrak{F}}}} \right)^3 + \left(\mathscr{t}_{\tilde{\tilde{\mathfrak{F}}}} \right)^3 \tag{5}$$

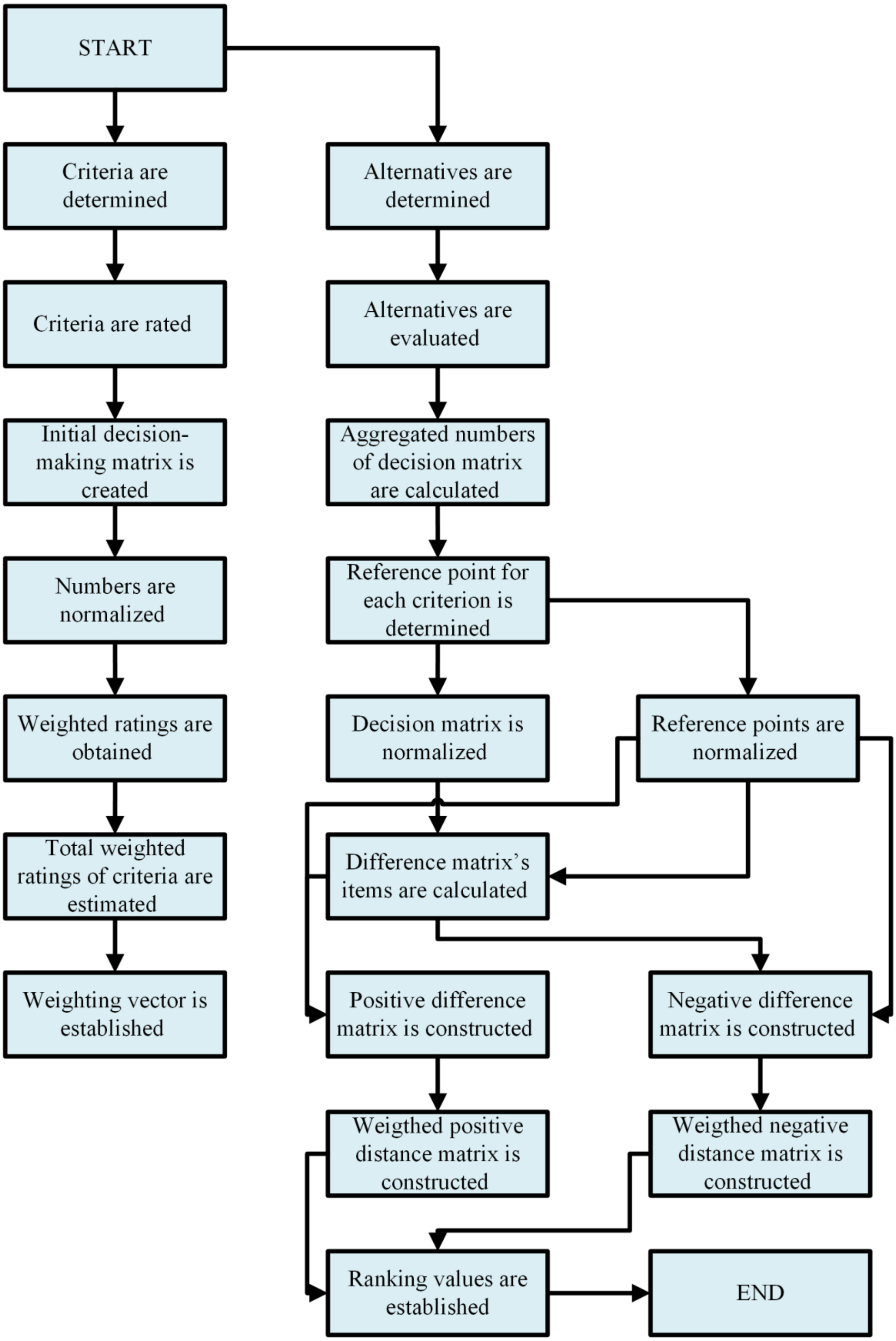

Fig. 1. Methodology

Let $\widetilde{\mathfrak{F}} = \left(s_{\widetilde{\mathfrak{F}}}, t_{\widetilde{\mathfrak{F}}}\right)$, $\widetilde{\mathfrak{F}}_1 = \left(s_{\widetilde{\mathfrak{F}}_1}, t_{\widetilde{\mathfrak{F}}_1}\right)$ and $\widetilde{\mathfrak{F}}_2 = \left(s_{\widetilde{\mathfrak{F}}_2}, t_{\widetilde{\mathfrak{F}}_2}\right)$ be any three FFNs and ξ is positive number. Then, some operations for these numbers are defined as in Equations (6) – (9).

$$\widetilde{\mathfrak{F}}_1 \oplus \widetilde{\mathfrak{F}}_2 = \left(\sqrt[3]{\left(s_{\widetilde{\mathfrak{F}}_1}\right)^3 + \left(s_{\widetilde{\mathfrak{F}}_2}\right)^3 - \left(s_{\widetilde{\mathfrak{F}}_1}\right)^3\left(s_{\widetilde{\mathfrak{F}}_2}\right)^3}, t_{\widetilde{\mathfrak{F}}_1} t_{\widetilde{\mathfrak{F}}_2}\right) \tag{6}$$

$$\widetilde{\mathfrak{F}}_1 \otimes \widetilde{\mathfrak{F}}_2 = \left(s_{\widetilde{\mathfrak{F}}_1} s_{\widetilde{\mathfrak{F}}_2}, \sqrt[3]{\left(t_{\widetilde{\mathfrak{F}}_1}\right)^3 + \left(t_{\widetilde{\mathfrak{F}}_2}\right)^3 - \left(t_{\widetilde{\mathfrak{F}}_1}\right)^3\left(t_{\widetilde{\mathfrak{F}}_2}\right)^3}\right) \tag{7}$$

$$\xi \odot \widetilde{\mathfrak{F}} = \left(\sqrt[3]{1 - \left(1 - \left(s_{\widetilde{\mathfrak{F}}}\right)^3\right)^{\xi}}, \left(t_{\widetilde{\mathfrak{F}}}\right)^{\xi}\right) \tag{8}$$

$$\left(\widetilde{\mathfrak{F}}\right)^{\xi} = \left(\left(s_{\widetilde{\mathfrak{F}}}\right)^{\xi}, \sqrt[3]{1 - \left(1 - \left(t_{\widetilde{\mathfrak{F}}}\right)^3\right)^{\xi}}\right) \tag{9}$$

Assume that $\widetilde{\mathfrak{F}}_i = \left(s_{\widetilde{\mathfrak{F}}_i}, t_{\widetilde{\mathfrak{F}}_i}\right)$ $(i = 1,2, \dots, k)$ is a collection of FFNs. Then the Fermatean fuzzy weighted averaging operator is determined via Equation (10).

$$FFWA\left(\widetilde{\mathfrak{F}}_i\right) = \left(\sqrt[3]{1 - \prod_{i=1}^{k}\left(1 - \left(s_{\widetilde{\mathfrak{F}}}\right)^3\right)^{w_i}}, \prod_{i=1}^{k}\left(t_{\widetilde{\mathfrak{F}}}\right)^{w_i}\right) \tag{10}$$

Wherein $\sum w_i = 1$.

2.2. FF-SIWEC

SIWEC is a subjective method that uses standard deviation to calculate the weights of the criteria. Its application with FFNs can be expressed as follows [37]. SIWEC determines criteria weights from expert evaluations while incorporating the dispersion of these evaluations through standard deviation. The method begins with subjective information because the initial criterion assessments are provided by experts. However, the subsequent weighting procedure does not rely solely on directly assigned importance coefficients. After normalization, standard deviation is used to capture the degree of variation associated with the criterion evaluations, and this information contributes to the calculation of the final weights. Therefore, the use of standard deviation introduces a data-responsive component into an expert-based weighting process, but it does not transform the method into a purely objective weighting technique [38]. This distinction is consistent with the broader classification of criteria-weighting methods into subjective, objective, and hybrid or integrated structures discussed in recent MCDM weighting literature [39]. Related weighting developments also demonstrate the continuing importance of systematically deriving and reassessing criteria weights in complex decision problems [40].

After n criteria are determined, these criteria are rated by k evaluators. Using the FFN equivalents of these ratings, the initial decision-making matrix in Equation (11) is created.

$$\widetilde{H} = \begin{bmatrix} \tilde{\hbar}_{11} & \cdots & \tilde{\hbar}_{1n} \\ \vdots & \ddots & \vdots \\ \tilde{\hbar}_{k1} & \cdots & \tilde{\hbar}_{kn} \end{bmatrix} \tag{11}$$

Wherein $\tilde{\hbar}_{ij} = \left(s_{\tilde{\hbar}_{ij}}, t_{\tilde{\hbar}_{ij}}\right)$ denotes the FFN of rating of j^{th} criterion for i^{th} evaluator. Later, these numbers are normalized using Equation (12).

$$\mathfrak{y}_{ij} = \frac{\left(\frac{1+\left(s_{\tilde{\hbar}_{ij}}\right)^3-\left(t_{\tilde{\hbar}_{ij}}\right)^3}{2}\right)}{\max\left(\frac{1+\left(s_{\tilde{\hbar}_{ij}}\right)^3-\left(t_{\tilde{\hbar}_{ij}}\right)^3}{2}\right)} \tag{12}$$

Subsequently, the normalized ratings are multiplied by the standard deviation of normalized ratings. The weighted ratings are obtained with Equation (13).

$$\delta_{ij} = \mathfrak{y}_{ij} \times \sigma_i \tag{13}$$

Wherein σ is standard deviation and computed via Equation (14).

$$\sigma_i = \sqrt{\frac{1}{n}\sum_{j=1}^{n}\left(\mathfrak{y}_{ij} - \frac{1}{n}\sum_{j=1}^{n}\mathfrak{y}_{ij}\right)^2} \tag{14}$$

Afterwards, the total weighted ratings of criteria are estimated by Equation (15).

$$z_j = \sum_{i=1}^{k}\delta_{ij} \tag{15}$$

Finally, the weighting vector is established as in Equation (16).

$$\vartheta_j = \frac{z_j}{\sum_{j=1}^{n} z_j} \tag{16}$$

2.3. FF-IRPA

Based on the use of satisfaction functions in the decision-making process, the IRPA method allows for a more realistic evaluation of alternatives using a reference set approach. In this approach, it is assumed that evaluator satisfaction increases non-linearly after threshold values, and the reference set allows for analysis in different versions by selecting average, maximum, or minimum values. Furthermore, this approach assumes that reaching the reference value is more important than exceeding it, and that utility varies non-linearly. Thus, IRPA is considered a strong alternative to traditional ranking models. Its application with FFNs can be expressed as follows [41].

After m alternatives are determined, these alternatives are evaluated by k evaluators. Using the FFN equivalents of these evaluations, the aggregated numbers of decision matrix are calculated using Equation (17).

$$\tilde{x}_{ij} = \left(\sqrt[3]{1-\prod_{p=1}^{k}\left(1-\left(s_{\tilde{x}_{ij}^{p}}\right)^3\right)^{1/k}}, \prod_{p=1}^{k}\left(t_{\tilde{x}_{ij}^{p}}\right)^{1/k}\right) \tag{17}$$

Wherein $\tilde{x}_{ij} = \left(s_{\tilde{x}_{ij}}, t_{\tilde{x}_{ij}}\right)$ denotes the averaging value of evaluations of i^{th} alternative regarding j^{th} criterion. Later, reference point for each criterion is determined with the help of Equation (18).

$$\widetilde{rp}_j = \left(\sqrt[3]{1-\prod_{i=1}^{m}\left(1-\left(s_{\tilde{x}_{ij}}\right)^3\right)^{1/m}}, \prod_{i=1}^{m}\left(t_{\tilde{x}_{ij}}\right)^{1/m}\right) \tag{18}$$

Afterwards, decision matrix is normalized using vector normalization process in Equation (19).

$$\mathfrak{z}_{ij}=\frac{\left(\frac{1+\left(s_{\tilde{x}_{ij}}\right)^{3}-\left(t_{\tilde{x}_{ij}}\right)^{3}}{2}\right)}{\sqrt{\sum_{i=1}^{m}\left(\frac{1+\left(s_{\tilde{x}_{ij}}\right)^{3}-\left(t_{\tilde{x}_{ij}}\right)^{3}}{2}\right)^{2}+\left(\frac{1+\left(s_{\widetilde{rp}_{j}}\right)^{3}-\left(t_{\widetilde{rp}_{j}}\right)^{3}}{2}\right)^{2}}} \tag{19}$$

Similarly, the reference points are normalized via Equation (20).

$$\mathfrak{z}rp_{j}=\frac{\left(\frac{1+\left(s_{\widetilde{rp}_{j}}\right)^{3}-\left(t_{\widetilde{rp}_{j}}\right)^{3}}{2}\right)}{\sqrt{\sum_{i=1}^{m}\left(\frac{1+\left(s_{\tilde{x}_{ij}}\right)^{3}-\left(t_{\tilde{x}_{ij}}\right)^{3}}{2}\right)^{2}+\left(\frac{1+\left(s_{\widetilde{rp}_{j}}\right)^{3}-\left(t_{\widetilde{rp}_{j}}\right)^{3}}{2}\right)^{2}}} \tag{20}$$

The difference matrix is created by Equation (21).

$$\Delta_{ij}=\mathfrak{z}_{ij}-\mathfrak{z}rp_{j} \tag{21}$$

Subsequently, the positive difference matrix is constructed with the help of Equations (21)-(23).

$$\Delta_{ij}^{+}=\begin{cases}\frac{\Delta_{ij}}{\mathfrak{z}rp_{j}} & ,\Delta_{ij}>0\\ 0 & ,\Delta_{ij}\leq 0\end{cases};if\ criterion\ is\ benefit \tag{22}$$

$$\Delta_{ij}^{+}=\begin{cases}0 & ,\Delta_{ij}\geq 0\\ \left|\frac{\Delta_{ij}}{\mathfrak{z}rp_{j}}\right| & ,\Delta_{ij}<0\end{cases};if\ criterion\ is\ cost \tag{23}$$

Likewise, the negative difference matrix is created with the help of Equations (24) and (25).

$$\Delta_{ij}^{-}=\begin{cases}\left|\frac{\Delta_{ij}}{\mathfrak{z}rp_{j}}\right| & ,\Delta_{ij}<0\\ 0 & ,\Delta_{ij}\geq 0\end{cases};if\ criterion\ is\ benefit \tag{24}$$

$$\Delta_{ij}^{-}=\begin{cases}0 & ,\Delta_{ij}\leq 0\\ \frac{\Delta_{ij}}{\mathfrak{z}rp_{j}} & ,\Delta_{ij}>0\end{cases};if\ criterion\ is\ cost \tag{25}$$

Afterwards, the weighted difference matrices are calculated by Equations (26) and (27), respectively.

$$\gamma_{ij}^{+}=\left(\vartheta_{j}\times\Delta_{ij}^{+}\right)^{(1-\vartheta_{j})} \tag{26}$$

$$\gamma_{ij}^{-}=\left(\vartheta_{j}\times\Delta_{ij}^{-}\right)^{(1-\vartheta_{j})} \tag{27}$$

After that, positive distance matrix is computed using Equation (28) and negative distance matrix is estimated via Equation (29).

$$\mathfrak{p}_{i}=\sum_{j=1}^{n}\gamma_{ij}^{+} \tag{28}$$

$$\mathfrak{n}_{i}=\sum_{j=1}^{n}\gamma_{ij}^{-} \tag{29}$$

Finally, the ranking values are established with Equation (30).

$$\mathfrak{r}_i = \frac{1}{2}(\mathfrak{p}_i - \mathfrak{n}_i) \tag{30}$$

The expert panel consisted of ten evaluators, each with at least 18 years of professional experience in marketing and related decision-making activities. The experts were selected purposively based on their extensive professional experience, knowledge of digital marketing practices, familiarity with strategic marketing decisions, and ability to assess marketing strategies across different business environments. The evaluation did not require specialized technical judgments regarding the operational or clinical characteristics of the three sectors, but rather focused on common digital marketing dimensions such as purchase intention, consumer confidence, brand loyalty, interaction, personalization, brand image, cost-effectiveness, measurability, and sustainability. Therefore, expertise in digital and strategic marketing was considered the primary qualification for participation. The same experts evaluated e-commerce, tourism, and healthcare to maintain consistency across the sectoral comparisons and to prevent differences in panel composition from influencing the comparative results. Their extensive marketing experience also enabled them to interpret how the importance of the common criteria and the suitability of the digital marketing strategies may differ across sectoral contexts.

3. Result

This part of this study presents the results of evaluation of the effectiveness of digital marketing strategies by sector.

3.1. Evaluation of E-commerce Sector

3.1.1. Weighting of Criteria

Criteria are selected as criteria from literature. These criteria are shown in Table 1 with abbreviations and types.

Table 1
Criteria with Abbreviations

Criterion	Type	Abb
Impact on Purchase Intention	B	IPI
Consumer Confidence	B	CCF
Potential for Building Brand Loyalty	B	BBL
Level of Interaction	B	LOI
Perceived Level of Personalization	B	PLP
Contribution to Brand Image	B	CBI
Cost-Effectiveness	B	CEF
Measurability and Ease of Analytical Tracking	B	MAT
Long-Term Sustainability	B	LTS

These criteria are benefit. These criteria are rated by 10 evaluators who have at least 18 years of experience in marketing. An initial decision-making matrix is created using the fuzzy numerical equivalents of these evaluators' ratings. This matrix is presented in Table 2.

Later, this initial decision-making matrix is normalized using Equation (12). The normalized decision-making matrix is illustrated in Table 3. Subsequently, the normalized decision-making ratings are multiplied by the standard deviation with Equations (13) and (14). Standard deviations of evaluators are equal to .055, .013, .060, .056, .045, .060, .052, .039, .032, and .038, respectively. The weighted decision-making matrix is displayed in Table 4.

Table 2
Initial Decision-making Matrix for E-commerce Sector

	IPI	CCF	BBL	LOI	PLP
E1	(0.15,0.85)	(0.75,0.25)	(0.85,0.15)	(0.25,0.65)	(0.5,0.45)
E2	(0.5,0.45)	(0.5,0.45)	(0.65,0.35)	(0.5,0.45)	(0.65,0.35)
E3	(0.15,0.85)	(0.5,0.45)	(0.85,0.15)	(0.25,0.65)	(0.5,0.45)
E4	(0.15,0.85)	(0.25,0.65)	(0.85,0.15)	(0.25,0.75)	(0.25,0.65)
E5	(0.25,0.65)	(0.65,0.35)	(0.75,0.25)	(0.5,0.45)	(0.25,0.75)
E6	(0.15,0.85)	(0.5,0.45)	(0.85,0.15)	(0.5,0.45)	(0.5,0.45)
E7	(0.25,0.65)	(0.75,0.25)	(0.75,0.25)	(0.25,0.75)	(0.25,0.65)
E8	(0.5,0.45)	(0.65,0.35)	(0.65,0.35)	(0.5,0.45)	(0.65,0.35)
E9	(0.25,0.65)	(0.25,0.65)	(0.75,0.25)	(0.5,0.45)	(0.5,0.45)
E10	(0.5,0.45)	(0.65,0.35)	(0.75,0.25)	(0.25,0.65)	(0.65,0.35)

	CBI	CEF	MAT	LTS
E1	(0.65,0.35)	(0.65,0.35)	(0.25,0.75)	(0.65,0.35)
E2	(0.5,0.45)	(0.65,0.35)	(0.25,0.75)	(0.5,0.45)
E3	(0.75,0.25)	(0.65,0.35)	(0.15,0.85)	(0.5,0.45)
E4	(0.5,0.45)	(0.75,0.25)	(0.25,0.75)	(0.25,0.65)
E5	(0.5,0.45)	(0.75,0.25)	(0.15,0.85)	(0.65,0.35)
E6	(0.25,0.65)	(0.75,0.25)	(0.15,0.85)	(0.65,0.35)
E7	(0.85,0.15)	(0.65,0.35)	(0.25,0.75)	(0.5,0.45)
E8	(0.85,0.15)	(0.75,0.25)	(0.15,0.85)	(0.5,0.45)
E9	(0.65,0.35)	(0.75,0.25)	(0.25,0.75)	(0.25,0.65)
E10	(0.75,0.25)	(0.65,0.35)	(0.15,0.85)	(0.5,0.45)

Table 3
Normalized Decision-making Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
E1	0.242	0.873	10.000	0.460	0.642	0.765	0.765	0.369	0.765
E2	0.642	0.642	0.765	0.642	0.765	0.642	0.765	0.369	0.642
E3	0.242	0.642	10.000	0.460	0.642	0.873	0.765	0.242	0.642
E4	0.242	0.460	10.000	0.369	0.460	0.642	0.873	0.369	0.460
E5	0.460	0.765	0.873	0.642	0.369	0.642	0.873	0.242	0.765
E6	0.242	0.642	10.000	0.642	0.642	0.460	0.873	0.242	0.765
E7	0.460	0.873	0.873	0.369	0.460	10.000	0.765	0.369	0.642
E8	0.642	0.765	0.765	0.642	0.765	10.000	0.873	0.242	0.642
E9	0.460	0.460	0.873	0.642	0.642	0.765	0.873	0.369	0.460
E10	0.642	0.765	0.873	0.460	0.765	0.873	0.765	0.242	0.642

Table 4
Weighted Decision-making Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
E1	0.057	0.204	0.234	0.108	0.150	0.179	0.179	0.086	0.179
E2	0.074	0.074	0.088	0.074	0.088	0.074	0.088	0.042	0.074
E3	0.059	0.158	0.245	0.113	0.158	0.214	0.188	0.059	0.158
E4	0.057	0.108	0.236	0.087	0.108	0.151	0.206	0.087	0.108
E5	0.097	0.162	0.185	0.136	0.078	0.136	0.185	0.051	0.162
E6	0.059	0.158	0.245	0.158	0.158	0.113	0.214	0.059	0.188
E7	0.105	0.199	0.199	0.084	0.105	0.227	0.174	0.084	0.146
E8	0.127	0.151	0.151	0.127	0.151	0.198	0.173	0.048	0.127
E9	0.083	0.083	0.157	0.115	0.115	0.137	0.157	0.066	0.083
E10	0.124	0.148	0.169	0.089	0.148	0.169	0.148	0.047	0.124

Afterwards, the total weighted ratings of criteria are estimated by Equation (15). Finally, the weighting vector is established as in Equation (16). The results are summarized in Table 5. According to ϑ values in Table 5, the most critical criteria are potential for building brand loyalty with .161 and cost-effectiveness with .145, respectively.

Table 5
Total Weighted Ratings and Weighting Vector for E-commerce Sector

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
z	0.842	10.444	10.909	10.090	10.259	10.599	10.711	0.630	10.348
ϑ	0.071	0.122	0.161	0.092	0.106	0.135	0.145	0.053	0.114

3.1.2. Ranking of Digital Marketing Strategies

As an alternative set, strategies that directly align with current digital advertising practices are identified. These digital marketing strategies with abbreviations are given in Table 6.

Table 6
Digital Marketing Strategies

Digital Marketing Strategy	Abb
Social Media Marketing	SMMK
Influencer Marketing	INFM
Content Marketing	CMRK
Email and Direct Digital Marketing	EDDM
Programmatic and Targeted Digital Advertising	PTDA
AI-Powered Personalized Marketing	AIPM

These strategies are then appropriately evaluated by the same ten evaluators. Using the FFN equivalents of these evaluations, the aggregated numbers of decision matrix are calculated using Equation (17). The decision matrix is given in Table 7.

Table 7
Decision Matrix for E-commerce Sector

	IPI	CCF	BBL	LOI	PLP
SMMK	(0.463,0.586)	(0.487,0.517)	(0.47,0.55)	(0.494,0.552)	(0.739,0.278)
INFM	(0.428,0.571)	(0.51,0.497)	(0.518,0.503)	(0.457,0.557)	(0.612,0.385)
CMRK	(0.612,0.406)	(0.572,0.447)	(0.534,0.481)	(0.457,0.557)	(0.562,0.446)
EDDM	(0.667,0.333)	(0.635,0.359)	(0.689,0.311)	(0.657,0.341)	(0.368,0.616)
PTDA	(0.787,0.214)	(0.798,0.204)	(0.798,0.204)	(0.826,0.175)	(0.221,0.789)
AIPM	(0.656,0.344)	(0.705,0.3)	(0.761,0.245)	(0.763,0.241)	(0.362,0.632)

	CBI	CEF	MAT	LTS
SMMK	(0.504,0.552)	(0.707,0.298)	(0.37,0.683)	(0.509,0.504)
INFM	(0.384,0.642)	(0.581,0.425)	(0.488,0.503)	(0.488,0.51)
CMRK	(0.587,0.436)	(0.51,0.512)	(0.472,0.559)	(0.61,0.394)
EDDM	(0.594,0.39)	(0.416,0.549)	(0.7,0.301)	(0.646,0.35)
PTDA	(0.818,0.184)	(0.221,0.789)	(0.818,0.184)	(0.808,0.194)
AIPM	(0.792,0.212)	(0.331,0.656)	(0.724,0.281)	(0.74,0.267)

Behind, reference point for each Criterion is determined with the help of Equation (18). The result is summarized in Table 8. Afterwards, decision matrix is normalized using Equation (19). The normalized decision matrix is exhibited in Table 9.

Table 8
Reference Point

IPI	CCF	BBL	LOI	PLP
(0.638,0.387)	(0.648,0.369)	(0.667,0.357)	(0.664,0.368)	(0.549,0.495)
CBI	CEF	MAT	LTS	
(0.669,0.365)	(0.522,0.514)	(0.655,0.379)	(0.666,0.35)	

Table 9
Normalized Decision Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
SMMK	0.288	0.307	0.289	0.298	0.518	0.299	0.513	0.233	.308
INFM	0.286	0.317	0.312	0.289	0.439	0.247	0.433	0.316	.302
CMRK	0.373	0.345	0.321	0.289	0.408	0.349	0.386	0.297	.357
EDDM	0.404	0.380	0.400	0.390	0.305	0.359	0.351	0.420	.376
PTDA	0.474	0.471	0.462	0.489	0.195	0.481	0.201	0.491	.466
AIPM	0.399	0.416	0.440	0.448	0.298	0.464	0.292	0.433	.425

Likewise, the reference points are normalized via Equation (20). The normalized reference points are expressed in Table 10.

Table 10
Normalized Reference Points

IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
0.386	0.384	0.386	0.390	0.391	0.390	0.389	0.391	0.384

Behind, the difference matrix's items are calculated by Equation (21). The difference matrix is shown in Table 11.

Table 11
Difference Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
SMMK	-0.097	-0.077	-0.097	-0.091	0.127	-0.091	0.124	-0.158	-0.076
INFM	-0.099	-0.067	-0.074	-0.100	0.048	-0.143	0.044	-0.075	-0.083
CMRK	-0.013	-0.039	-0.065	-0.100	0.017	-0.041	-0.003	-0.094	-0.027
EDDM	0.019	-0.004	0.014	0.000	-0.086	-0.031	-0.039	0.029	-0.008
PTDA	0.089	0.087	0.077	0.099	-0.196	0.090	-0.188	0.100	0.082
AIPM	0.013	0.032	0.054	0.058	-0.093	0.074	-0.098	0.042	0.041

Subsequently, the positive difference matrix is constructed with the help of Equations (22) and (23). For this, types of criteria are given in Table 1. The positive difference matrix is illustrated in Table 12.

Table 12
Positive Difference Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
SMMK	0.000	0.000	0.000	0.000	0.324	0.000	0.319	0.000	0.000
INFM	0.000	0.000	0.000	0.000	0.123	0.000	0.112	0.000	0.000
CMRK	0.000	0.000	0.000	0.000	0.043	0.000	0.000	0.000	0.000
EDDM	0.049	0.000	0.037	0.000	0.000	0.000	0.000	0.073	0.000
PTDA	0.230	0.227	0.199	0.254	0.000	0.232	0.000	0.256	0.213
AIPM	0.034	0.083	0.140	0.150	0.000	0.189	0.000	0.108	0.106

Likewise, the negative difference matrix is created with the help of Equations (24) and (25). This matrix is shared in Table 13. Afterwards, these matrices are multiplied and powered by weighting vector according to Equations (26) and (27). The weighted positive difference matrix is presented in Table 14.

Table 13
Negative Difference Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
SMMK	0.252	0.200	0.251	0.234	0.000	0.233	0.000	0.403	0.199
INFM	0.257	0.174	0.192	0.258	0.000	0.367	0.000	0.193	0.215
CMRK	0.033	0.102	0.168	0.258	0.000	0.105	0.008	0.241	0.070
EDDM	0.000	0.010	0.000	0.000	0.219	0.080	0.099	0.000	0.021
PTDA	0.000	0.000	0.000	0.000	0.502	0.000	0.483	0.000	0.000
AIPM	0.000	0.000	0.000	0.000	0.239	0.000	0.251	0.000	0.000

Table 14
Weighted Positive Difference Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
SMMK	0.000	0.000	0.000	0.000	0.049	0.000	0.072	0.000	0.000
INFM	0.000	0.000	0.000	0.000	0.021	0.000	0.029	0.000	0.000
CMRK	0.000	0.000	0.000	0.000	0.008	0.000	0.000	0.000	0.000
EDDM	0.005	0.000	0.014	0.000	0.000	0.000	0.000	0.005	0.000
PTDA	0.022	0.043	0.056	0.033	0.000	0.050	0.000	0.017	0.037
AIPM	0.004	0.018	0.042	0.020	0.000	0.042	0.000	0.008	0.020

Similarly, the weighted negative difference matrix is given in Table 15.

Table 15
Weighted Negative Difference Matrix

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
SMMK	0.024	0.038	0.068	0.031	0.000	0.050	0.000	0.026	0.035
INFM	0.024	0.034	0.054	0.034	0.000	0.074	0.000	0.013	0.037
CMRK	0.004	0.021	0.049	0.034	0.000	0.025	0.003	0.016	0.014
EDDM	0.000	0.003	0.000	0.000	0.035	0.020	0.026	0.000	0.005
PTDA	0.000	0.000	0.000	0.000	0.073	0.000	0.103	0.000	0.000
AIPM	0.000	0.000	0.000	0.000	0.038	0.000	0.059	0.000	0.000

Behind, positive and negative distance matrices are computed using Equations (28) and (29), respectively. The results are summarized in Table 16.

Table 16
Positive and Negative Distance Matrices

	$\mathfrak{p}$	$\mathfrak{n}$
SMMK	0.121	0.272
INFM	0.050	0.271
CMRK	0.008	0.165
EDDM	0.024	0.089
PTDA	0.258	0.176
AIPM	0.153	0.096

Finally, the ranking values of digital marketing strategies are established with Equation (30). The results are visualized in Figure 2. When Figure 2 is examined, the most suitable digital marketing strategy is programmatic and targeted digital advertising with 0.041.

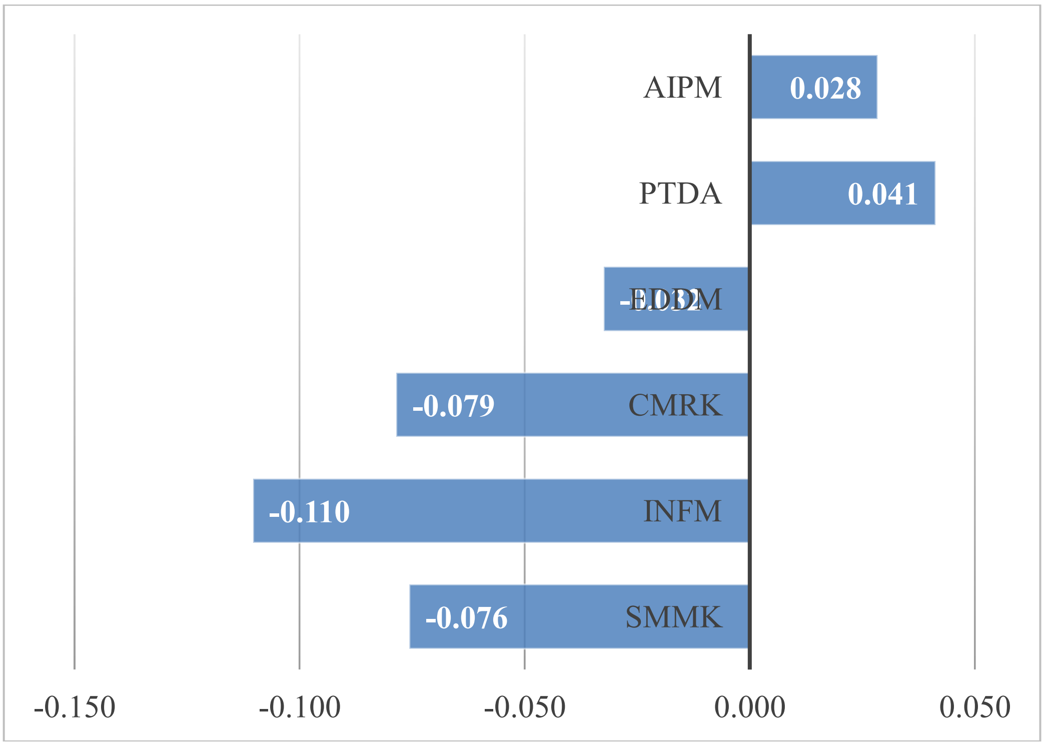

Fig. 2. Ranking Values of Digital Marketing Strategies for E-commerce Sector

3.2. Evaluation of Tourism Sector
3.2.1. Weighting of Criteria

Evaluators also provide ratings for the tourism sector. An initial decision-making matrix is created using the fuzzy numerical equivalents of these evaluators' ratings. This matrix is presented in Table 17.

Table 17
Initial Decision-making Matrix for Tourism Sector

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
E1	(0.25,0.65)	(0.25,0.65)	(0.25,0.75)	(0.75,0.25)	(0.85,0.15)	(0.25,0.75)	(0.25,0.65)	(0.25,0.65)	(0.5,0.45)
E2	(0.5,0.45)	(0.65,0.35)	(0.25,0.75)	(0.75,0.25)	(0.75,0.25)	(0.25,0.65)	(0.25,0.75)	(0.5,0.45)	(0.85,0.15)
E3	(0.25,0.75)	(0.65,0.35)	(0.25,0.65)	(0.65,0.35)	(0.85,0.15)	(0.25,0.65)	(0.65,0.35)	(0.65,0.35)	(0.85,0.15)
E4	(0.5,0.45)	(0.65,0.35)	(0.25,0.65)	(0.65,0.35)	(0.75,0.25)	(0.25,0.65)	(0.5,0.45)	(0.75,0.25)	(0.75,0.25)
E5	(0.25,0.75)	(0.25,0.65)	(0.15,0.85)	(0.75,0.25)	(0.85,0.15)	(0.25,0.75)	(0.25,0.75)	(0.75,0.25)	(0.65,0.35)
E6	(0.5,0.45)	(0.65,0.35)	(0.25,0.75)	(0.5,0.45)	(0.65,0.35)	(0.15,0.85)	(0.65,0.35)	(0.65,0.35)	(0.85,0.15)
E7	(0.25,0.65)	(0.25,0.65)	(0.25,0.75)	(0.75,0.25)	(0.65,0.35)	(0.25,0.75)	(0.5,0.45)	(0.5,0.45)	(0.75,0.25)
E8	(0.5,0.45)	(0.65,0.35)	(0.15,0.85)	(0.65,0.35)	(0.75,0.25)	(0.25,0.75)	(0.5,0.45)	(0.65,0.35)	(0.85,0.15)
E9	(0.25,0.65)	(0.25,0.65)	(0.25,0.75)	(0.65,0.35)	(0.75,0.25)	(0.25,0.75)	(0.25,0.75)	(0.75,0.25)	(0.75,0.25)
E10	(0.25,0.65)	(0.5,0.45)	(0.25,0.75)	(0.5,0.45)	(0.65,0.35)	(0.25,0.65)	(0.5,0.45)	(0.5,0.45)	(0.85,0.15)

The criterion weights are obtained by following the steps of the SIWEC method. The final results are summarized in Table 18.

Table 18
Total Weighted Ratings and Weighting Vector for Tourism Sector

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
z	1.071	1.314	.747	1.656	1.861	.818	1.170	1.541	1.891
ϑ	.089	.109	.062	.137	.154	.068	.097	.128	.157

According to ϑ values in Table 18, the most critical criteria for tourism sector are potential for long-term sustainability with .157 and perceived level of personalization with .154, respectively.

3.2.2. Ranking of Digital Marketing Strategies

Evaluators also provide evaluations for the tourism sector. Thus, the aggregated numbers of decision matrix are calculated using Equation (17). The decision matrix for tourism sector is exhausted in Table 19.

Table 19
Decision Matrix for Tourism Sector

	IPI	CCF	BBL	LOI	PLP
SMMK	(0.229,0.746)	(0.192,0.796)	(0.229,0.757)	(0.212,0.765)	(0.221,0.745)
INFM	(0.503,0.492)	(0.553,0.444)	(0.53,0.492)	(0.51,0.49)	(0.523,0.48)
CMRK	(0.393,0.569)	(0.436,0.529)	(0.416,0.565)	(0.338,0.639)	(0.25,0.708)
EDDM	(0.627,0.387)	(0.637,0.366)	(0.714,0.292)	(0.596,0.398)	(0.488,0.496)
PTDA	(0.662,0.345)	(0.691,0.311)	(0.728,0.295)	(0.725,0.281)	(0.693,0.33)
AIPM	(0.73,0.276)	(0.714,0.291)	(0.747,0.258)	(0.774,0.229)	(0.754,0.25)
	CBI	**CEF**	**MAT**	**LTS**	
SMMK	(0.192,0.807)	(0.212,0.754)	(0.221,0.766)	(0.236,0.696)	
INFM	(0.447,0.551)	(0.416,0.549)	(0.497,0.524)	(0.407,0.593)	
CMRK	(0.416,0.565)	(0.393,0.577)	(0.393,0.586)	(0.436,0.529)	
EDDM	(0.596,0.398)	(0.617,0.389)	(0.656,0.355)	(0.614,0.397)	
PTDA	(0.696,0.323)	(0.761,0.247)	(0.666,0.349)	(0.661,0.362)	
AIPM	(0.76,0.245)	(0.801,0.204)	(0.779,0.225)	(0.812,0.19)	

The rankings of digital marketing strategies are obtained by following the steps of the IRPA method. The result is visualized in Figure 3.

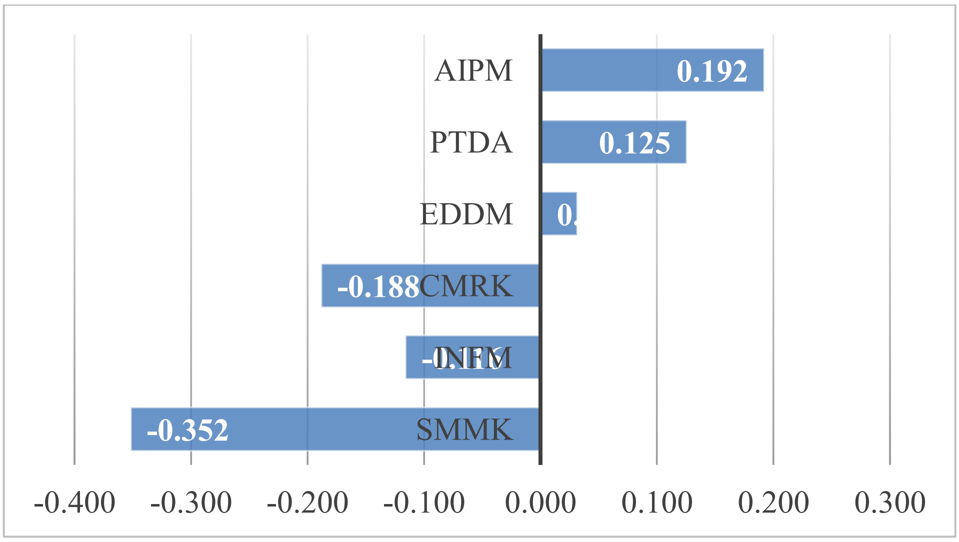

Fig. 3. Ranking Values of Digital Marketing Strategies for Tourism Sector

When Figure 3 is examined, the most suitable digital marketing strategy for this sector is AI-Powered personalized marketing with 0.192.

3.3. Evaluation of Healthcare Sector
3.3.1. Weighting of Criteria

Evaluators also provide ratings for the healthcare sector. An initial decision-making matrix is created using the fuzzy numerical equivalents of these evaluators' ratings. This matrix is presented in Table 20.

Table 20
Initial Decision-making Matrix for Healthcare Sector

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
E1	(0.25,0.65)	(0.5,0.45)	(0.25,0.65)	(0.25,0.65)	(0.75,0.25)	(0.75,0.25)	(0.75,0.25)	(0.75,0.25)	(0.65,0.35)
E2	(0.25,0.65)	(0.85,0.15)	(0.25,0.75)	(0.5,0.45)	(0.75,0.25)	(0.5,0.45)	(0.75,0.25)	(0.75,0.25)	(0.65,0.35)
E3	(0.5,0.45)	(0.5,0.45)	(0.25,0.65)	(0.5,0.45)	(0.5,0.45)	(0.65,0.35)	(0.75,0.25)	(0.85,0.15)	(0.65,0.35)
E4	(0.5,0.45)	(0.85,0.15)	(0.15,0.85)	(0.25,0.65)	(0.5,0.45)	(0.75,0.25)	(0.75,0.25)	(0.85,0.15)	(0.65,0.35)
E5	(0.25,0.75)	(0.85,0.15)	(0.25,0.65)	(0.5,0.45)	(0.5,0.45)	(0.5,0.45)	(0.65,0.35)	(0.75,0.25)	(0.65,0.35)
E6	(0.5,0.45)	(0.75,0.25)	(0.5,0.45)	(0.25,0.65)	(0.75,0.25)	(0.65,0.35)	(0.75,0.25)	(0.75,0.25)	(0.5,0.45)
E7	(0.5,0.45)	(0.65,0.35)	(0.5,0.45)	(0.25,0.75)	(0.75,0.25)	(0.65,0.35)	(0.65,0.35)	(0.65,0.35)	(0.5,0.45)
E8	(0.5,0.45)	(0.75,0.25)	(0.5,0.45)	(0.5,0.45)	(0.25,0.65)	(0.5,0.45)	(0.75,0.25)	(0.85,0.15)	(0.65,0.35)
E9	(0.25,0.75)	(0.85,0.15)	(0.25,0.65)	(0.25,0.75)	(0.25,0.65)	(0.75,0.25)	(0.75,0.25)	(0.65,0.35)	(0.65,0.35)
E10	(0.25,0.75)	(0.5,0.45)	(0.15,0.85)	(0.5,0.45)	(0.5,0.45)	(0.5,0.45)	(0.75,0.25)	(0.85,0.15)	(0.5,0.45)

The criterion weights are obtained by following the steps of the SIWEC method. The final results are summarized in Table 21.

Table 21
Total Weighted Ratings and Weighting Vector for Healthcare Sector

	IPI	CCF	BBL	LOI	PLP	CBI	CEF	MAT	LTS
z	0.933	10.565	0.803	0.972	10.256	10.377	10.563	10.654	10.339
ϑ	0.081	0.137	0.070	0.085	0.110	0.120	0.136	0.144	0.117

According to ϑ values in Table 21, the most critical criteria for healthcare sector are measurability and ease of analytical tracking with .144 and consumer confidence with .137, respectively.

3.3.2. Ranking of Digital Marketing Strategies

Evaluators also provide evaluations for the healthcare sector. Thus, the aggregated numbers of decision matrix are calculated using Equation (17). The decision matrix for tourism sector is exhausted in Table 22. The rankings of digital marketing strategies are obtained by following the steps of the IRPA method. The result is visualized in Figure 4.

When Figure 4 is examined, the most suitable digital marketing strategy for healthcare sector is programmatic and targeted digital advertising with 0.171.

A cross-sector comparison reveals that the preferred digital marketing strategy is not uniform across the three sectors, and this difference can be interpreted together with the sector-specific criteria weights. PTDA ranks first in e-commerce, where brand loyalty and cost-effectiveness receive the highest weights. This result suggests that e-commerce firms benefit from strategies that can efficiently target relevant consumer segments while supporting repeated interactions and longerterm customer relationships. In tourism, by contrast, long-term sustainability and perceived personalization emerge as the two most influential criteria, while AIPM becomes the highest-ranked strategy.

Table 22
Decision Matrix for Healthcare Sector

	IPI	CCF	BBL	LOI	PLP
SMMK	(0.553,0.438)	(0.447,0.527)	(0.575,0.432)	(0.523,0.466)	(0.497,0.502)
INFM	(0.334,0.657)	(0.388,0.601)	(0.323,0.692)	(0.388,0.609)	(0.356,0.657)
CMRK	(0.601,0.425)	(0.534,0.481)	(0.545,0.489)	(0.631,0.403)	(0.479,0.532)
EDDM	(0.7,0.301)	(0.654,0.344)	(0.576,0.404)	(0.667,0.333)	(0.623,0.368)
PTDA	(0.767,0.239)	(0.707,0.298)	(0.821,0.181)	(0.754,0.252)	(0.658,0.341)
AIPM	(0.595,0.431)	(0.657,0.341)	(0.546,0.451)	(0.643,0.367)	(0.546,0.451)
	(0.569,0.427)	(0.503,0.478)	(0.428,0.547)	(0.542,0.454)	
SMMK	(0.409,0.603)	(0.311,0.729)	(0.327,0.674)	(0.391,0.593)	
INFM	(0.518,0.503)	(0.596,0.414)	(0.556,0.472)	(0.566,0.455)	
CMRK	(0.646,0.35)	(0.632,0.362)	(0.591,0.393)	(0.632,0.362)	
EDDM	(0.748,0.258)	(0.774,0.231)	(0.773,0.233)	(0.718,0.286)	
PTDA	(0.638,0.378)	(0.63,0.369)	(0.552,0.456)	(0.617,0.389)	
AIPM	(0.569,0.427)	(0.503,0.478)	(0.428,0.547)	(0.542,0.454)	

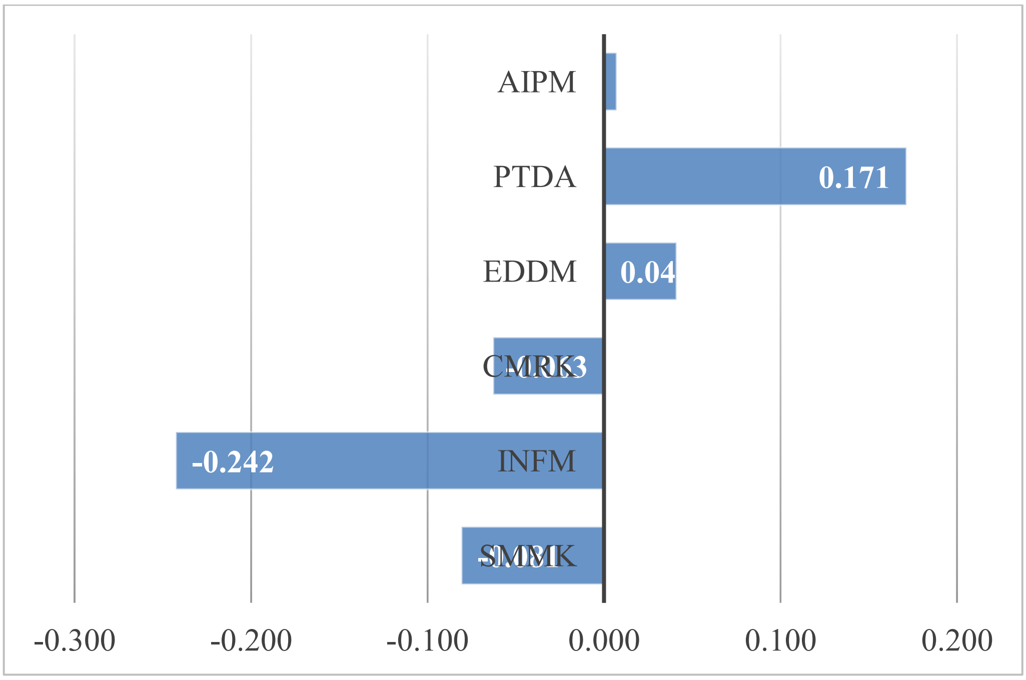

Fig. 4. Ranking Values of Digital Marketing Strategies for Healthcare Sector

This combination indicates that tourism marketing places greater emphasis on tailoring digital communication to individual preferences and maintaining customer-oriented interactions over time. Healthcare presents a different structure, with measurability and analytical tracking, consumer confidence, and cost-effectiveness receiving relatively high importance, while PTDA ranks first. In this context, targeted digital advertising can provide a more controllable and measurable mechanism for reaching specific audiences, although its implementation should remain sensitive to the trust-related characteristics of healthcare communication. These differences demonstrate that the effectiveness of a digital marketing strategy depends on the decision priorities of the sector rather than on the universal superiority of a single strategy. From a managerial perspective, e-commerce firms should emphasize measurable targeting and customer retention, tourism organizations should prioritize personalized customer experiences, and healthcare organizations should combine targeted communication with strong measurability and consumer confidence considerations.

For comparative analysis, TOPSIS and ARAS models are used. In addition, Spearman rank correlation coefficients between our model and these models are computed. Results are presented in Table 23.

Table 23
Comparative Analysis

	E-Commerce		Tourism		Healthcare	
	TOPSIS	ARAS	TOPSIS	ARAS	TOPSIS	ARAS
SMMK	4	3	6	6	5	5
INFM	6	6	4	5	6	6
CMRK	5	5	5	4	4	2
EDDM	3	4	3	3	2	4
PTDA	1	1	2	2	1	1
AIPM	2	2	1	1	3	3
Spearman	1.000	0.943	1.000	0.943	1.000	0.771

When Table 23 examined, the ranking results are valid. In addition, sensitivity analysis is applied with Monte Carlo simulation. Ten different weighting scenarios are constructed using Monte Carlo analysis, based on the criterion weights of each sector. Alternatives are ranked according to each weighting scenario, and their sensitivity to the criterion weights is tested. The results of the sensitivity analysis are given in Table 24.

Table 24
Sensitivity Analysis

E-Commerce	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10
SMMK	4	4	4	4	4	4	4	4	4	4
INFM	6	6	6	6	6	6	6	6	6	6
CMRK	5	5	5	5	5	5	5	5	5	5
EDDM	3	3	3	3	3	3	3	3	3	3
PTDA	1	1	1	1	1	1	1	1	1	1
AIPM	2	2	2	2	2	2	2	2	2	2
Tourism	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10
SMMK	6	6	6	6	6	6	6	6	6	6
INFM	4	4	4	4	4	4	4	4	4	4
CMRK	5	5	5	5	5	5	5	5	5	5
EDDM	3	3	3	3	3	3	3	3	3	3
PTDA	2	2	2	2	2	2	2	2	2	2
AIPM	1	1	1	1	1	1	1	1	1	1
Healthcare	SC1	SC2	SC3	SC4	SC5	SC6	SC7	SC8	SC9	SC10
SMMK	5	5	5	5	5	5	5	5	5	5
INFM	6	6	6	6	6	6	6	6	6	6
CMRK	4	4	4	4	4	4	4	4	4	4
EDDM	2	2	2	2	2	2	2	2	2	2
PTDA	1	1	1	1	1	1	1	1	1	1
AIPM	3	3	3	3	3	3	3	3	3	3

According to sensitivity results in Table 24, the ranking results are robust.

4. Conclusion

The results reveal a clear divergence in the prioritization of digital marketing strategies across sectors. Programmatic and targeted digital advertising emerges as the most suitable strategy for both e-commerce and healthcare, while AI-powered personalized marketing ranks first in the tourism sector. This difference can be explained by the nature of customer interactions and decision-making processes in each sector. In e-commerce, consumers are exposed to a wide range of products and often make quick purchase decisions [42]. Therefore, highly targeted and data-driven advertising enables firms to reach the right customer at the right time, increasing conversion rates. Similarly, in the healthcare sector, reaching specific patient groups with precise and reliable information is critical. Programmatic advertising allows institutions to communicate tailored messages while maintaining efficiency and compliance [43]. In contrast, tourism decisions are more experience-oriented and emotionally driven. AI-powered personalized marketing can analyze individual preferences and past behaviors to create customized travel suggestions, which enhances perceived value and engagement. These findings suggest that firms should align their digital marketing strategies with sector-specific consumer behavior. While data-driven targeting is essential in efficiency-focused sectors, personalization plays a more central role in experience-driven industries such as tourism [44].

The analysis of criteria weights also highlights important sectoral differences in strategic priorities. For the e-commerce sector, the most critical criterion is the potential for building brand loyalty. This reflects the highly competitive nature of online markets, where retaining customers is often more valuable than acquiring new ones. Firms can address this by implementing loyalty programs, personalized offers, and consistent brand communication [45]. In the tourism sector, the potential for long-term sustainability is the most important criterion. This indicates that businesses in this sector prioritize maintaining long-term relationships with customers and ensuring the continuity of demand. Sustainable marketing practices, such as promoting eco-friendly tourism and building trust through authentic content, can support this goal. In the healthcare sector, the most critical criteria are measurability and ease of analytical tracking, along with consumer confidence [46]. This reflects the need for accountability and trust in healthcare services. Organizations must ensure that their marketing efforts are transparent, data-driven, and aligned with ethical standards. Overall, these differences imply that businesses should not rely on a single set of criteria when designing digital marketing strategies. Instead, they must consider sector-specific dynamics and prioritize criteria that best reflect their operational realities [47].

This study seeks to identify the most appropriate digital marketing strategies for different types of businesses by considering multiple criteria within a comprehensive decision-making framework. To achieve this objective, sector-specific models were developed for the e-commerce, tourism, and healthcare industries. The study employs a hybrid methodology integrating the SIWEC technique for determining criteria weights and the Interactive Reference Point approach for ranking alternatives. In addition, Fermatean fuzzy numbers were incorporated to better capture uncertainty in the decision-making process. The analysis results indicate that programmatic and targeted digital advertising is the most suitable strategy for both e-commerce and healthcare sectors, while AI-powered personalized marketing is the most effective strategy for the tourism sector. Furthermore, the findings reveal that the importance of evaluation criteria differs significantly across sectors, highlighting the need for tailored strategic approaches. These results contribute to the literature by offering a novel sector-based evaluation of digital marketing strategies using an advanced fuzzy decision-making model. Unlike previous studies that provide generalized insights, this research presents a more detailed and context-specific analysis, thereby enhancing both methodological depth and practical relevance.

This study has several limitations that should be acknowledged. From a theoretical perspective, the analysis is limited to three sectors, which may restrict the generalizability of the findings to other industries. Additionally, the selection of criteria and strategies is based on existing literature and expert judgments, which may introduce subjectivity even though efforts were made to balance it with objective techniques. Regarding the proposed model, although the integration of SIWEC, the Interactive Reference Point approach, and Fermatean fuzzy numbers provides a robust framework, it also increases the complexity of the analysis. This complexity may limit its applicability for practitioners who lack technical expertise. Furthermore, the model assumes that the criteria are relatively stable, whereas in real-world settings, digital marketing environments are highly dynamic. Future studies can address these limitations by expanding the analysis to additional sectors and incorporating larger and more diverse expert groups. Moreover, alternative fuzzy sets or decision-making techniques can be compared to test the robustness of the results. Simplifying the model structure or developing user-friendly decision support systems may also enhance its practical usability.

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Conflicts of Interest
The authors declare no conflicts of interest.

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