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Evaluation of Suitable Accounting and Auditing Firms for SMEs in the Textile Industry with Picture Fuzzy Set-based Entropy & MARCOS Approach

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ABSTRACT

In today's highly competitive and dynamic business environment, selecting appropriate accounting and auditing service providers is critical for the sustainable growth and regulatory compliance of small and medium-sized enterprises (SMEs), particularly in the textile industry. This study proposes an integrated multi-criteria decision-making (MCDM) framework based on Picture Fuzzy Sets (PFS), Entropy, and the Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS) method to evaluate and rank suitable accounting and auditing firms for textile SMEs. Picture Fuzzy Sets are employed to model the inherent uncertainty and hesitancy in expert judgments more effectively, while the entropy method is utilized to determine objective weights for evaluation criteria. The MARCOS approach is then applied to assess and prioritize alternatives based on ideal and anti-ideal solutions. The proposed model is demonstrated through a case study involving expert evaluations from textile sector representatives and financial professionals. The results provide actionable insights for SMEs in selecting optimal accounting and auditing partners, and the robustness of the model is verified through sensitivity and comparative analyses. This study contributes to the literature by offering a novel and practical decision-support framework tailored to the specific needs of SMEs in a key industrial sector.

1. Introduction

In many decision-making problems today, making decisions based on complete and precise information may not always be possible. The main reason for this situation is the uncertainties frequently encountered in decision-making processes. These uncertainties can lead to decisions with incomplete or insufficient information, which can adversely affect the accuracy and effectiveness of the decisions made. To overcome this problem, Zadeh [1] developed the classical fuzzy set theory.

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According to this theory, decision-makers' preferences can take a value between 0 and 1, and these preferences can be expressed through membership functions. Zadeh's approach allows decision-makers to define their preferences more flexibly despite uncertainty. The classical fuzzy set approach, pioneered by Zadeh, was developed by researchers in later years and restructured in different ways. One of these developments is the intuitive fuzzy set theory put forward by Atanassov [2]. Heuristic fuzzy sets consider not only the individual characteristics of the decision maker, such as knowledge and experience, but also the hesitations they experience when deciding. They provide a more comprehensive evaluation by incorporating this element of uncertainty into the model.

Intuitionistic fuzzy sets (IFS) [3] and other fuzzy set methods aim to overcome the structural limitations of classical fuzzy set theory. This approach tries to overcome the shortcomings of the classical approach based on the assumption that all decision-makers have similar characteristics by including the individual differences of decision-makers, for example, their tendencies, attitudes, and hesitations, in the evaluation process, especially in decision-making processes with intense uncertainty and complex structure.

Classical fuzzy sets, known as type-1 fuzzy sets and their various extensions, exhibit certain limitations in effectively capturing and managing uncertainty. Type-1 fuzzy sets typically rely solely on the membership function and operate if each element belongs to a specific set to a certain degree. However, this assumption becomes insufficient when dealing with ambiguous or highly uncertain scenarios, limiting the robustness of decision-making processes. To overcome these shortcomings, type-2 fuzzy sets have been introduced as a more advanced approach, capable of handling complex and multidimensional uncertainties more effectively than classical models [4]. Moreover, type-2 fuzzy sets provide significant advantages in addressing linguistic uncertainties [5].

In this context, Picture Fuzzy Sets (PFS), introduced by Cuong [6], offer a novel decision-making framework specifically designed to manage situations characterized by high levels of uncertainty. The PFS approach seeks to overcome the structural limitations of classical and derivative fuzzy set models. It can also be viewed as an enhanced extension of Intuitionistic Fuzzy Sets, initially proposed by Atanassov [2] [7]. At the core of this model lies the condition that the sum of membership (μ), non-membership (v), and hesitancy (π) degrees must always equal one ($\mu + v + \pi = 1$). This characteristic enables PFS to consider acceptance and rejection levels of alternatives and explicitly incorporate indecision into the evaluation process. Consequently, PFS allows decision-makers to express varying acceptance, rejection, and hesitation, thus providing a more realistic and comprehensive representation of preferences under uncertainty.

From this point of view, PF further expands decision-makers' evaluations and provides the opportunity to evaluate situations that lead to uncertainty from a broader perspective. When considering alternatives, decision-makers can determine the degree of indecision regardless of their degree of membership [8]. Academic circles increasingly prefer PF sets due to the advantages they provide. While the number of studies using extended decision-making approaches with the help of PF sets is increasing, the literature is expanding. A total of 614 studies have been found since 2015 in the literature review conducted using keywords in Web of Science, SCOPUS, Google Scholar, and Mendeley databases, and the number of studies has increased yearly, from 66 in 2020 to 155 in 2023.

In general, application to cyberterrorism attacks [9], customize hospital recommendations based on patient feedback [10], waste disposal site selection [11] the choice of medical diagnostic device [12,13], Evaluation of sectors to invest in [14], Aviation 4.0 and 3D printer selection [15], Evaluation of pedagogical systems [16], Evaluation of software quality [17], selection of machines producing surgical masks [18], choice of suppliers [19], selection of team leaders in an international audit firm [20], Evaluation of citizens' satisfaction levels with municipal services [21], COVID-19 vaccine selection [22], evaluation of supply chain sustainability in catastrophic outages [23].

This study includes applying a version of the MARCOS (Measurement of Alternatives and Ranking by Consensus Solution) method developed with Pythagorean Fuzzy (PF) sets. The MARCOS method, which was first developed by Stević and colleagues in 2020 [24], stands out as a powerful and reliable tool widely preferred in the decision-making literature. With its straightforward and practical algorithm, this method supports more balanced evaluations by helping to minimize overly subjective or inconsistent judgments made by decision-makers. The growing number of studies 67 to date—that have implemented the MARCOS approach reflects its increasing recognition and credibility within the academic decision-making community.

In this perspective, the MARCOS approach, which was expanded with the help of PF sets, was used to evaluate six independent accounting and auditing companies determined during the preliminary research process of a medium-sized textile enterprise in Turkey within the framework of 12 criteria defined because of field studies and literature review. Independent accounting companies are among the most critical stakeholders in textile enterprises, one of Turkey's largest industries. However, accounting procedures and practices produced by professional firms significantly affect the financial performance and efficiency of enterprises in the textile industry. In addition to textile companies, the proposed model for selecting accounting firms for businesses in other sectors can provide a roadmap to decision-makers. At the same time, it can enable all stakeholders in the textile industry to achieve higher performance and efficiency. In addition, the extended version of the "Importance of Criteria through Inter-Criteria Correlation" (CRITIC) method developed by Shannon and Weaver [25], based on PF sets, was preferred to determine the weights of the criteria in the study.

The rest of the study is organized as follows. The second part gives general definitions of PF sets, and the PF MARCOS model's basic algorithm and application steps are shown. In the third part, the proposed model is applied to evaluate accounting firms for textile enterprises, and in the last part, the results obtained are discussed and summarized. Finally, the theoretical contributions and limitations of the management, as well as the suggestions for future studies, are outlined in the last section.

2. The Suggested Model

The two powerful evaluation methods, Entropy and MARCOS approaches, have been extended with the help of picture fuzzy sets, which are an extension of heuristic fuzzy sets (IFS). Accordingly, decision-makers define their evaluations as yes, no, abstention, and rejection. It significantly considers the degree of impartiality of decision-makers in the evaluation process. As a result, decision-makers can make more accurate and reliable decisions. On the other hand, while decision-makers may pay special attention to some alternatives, they may or may not be interested in some alternatives at a lower level. As a result, PF sets provide decision-makers with a unique evaluation process and environment. The following is a primer on the proposed PF-based Entropy and MARCOS integrated model.

2.1 Preliminary Information on PFSs

As mentioned earlier, picture fuzzy sets (PFS) are an extension of intuitionistic fuzzy sets. In this framework, an element may or may not be a set member when defining PF sets. In addition, decisions or evaluations may involve a certain indecision or hesitation. PF sets assume that the sum of membership, non-membership, and hesitation degrees will equal a maximum of 1. The sum can also take a value of less than 1 in this context. A PF set can be expressed mathematically in the following figure.

Let A, which is mathematically represented in Eq. 1, be a non-empty set PF in space X. A PF set, $\mu_A(x), \eta_A(x), \nu_A(x) \in [0,1]$; [8,26,27]:

$$A = \{\langle x, \mu_A(x), \eta_A(x), \nu_A(x)\rangle | x \in X\} \tag{1}$$

Here, $\mu_A(x)$; When defining the positive degree of membership of x in the set A, $\eta_A(x)$; degree of impartiality, $\nu_A(x)$ defines the degree of negative membership. $\mu_A(x), \eta_A(x)$ and $\nu_A(x)$ degrees are expected to satisfy the condition defined in Eq. 2.

$$0 \leq \mu_A\ (x) + \eta_A\ (x) + \nu_A\ (x) \leq 1, \forall x \in X \tag{2}$$

Simić *et al.* [27] demonstrate that the rejection degree of x is $\pi_A(x) = 1 - (\mu_A(x) + \eta_A(x) + \nu_A(x))$ and three sets of values of A, A_1, and A_2, $A = \langle \mu_A(x), \eta_A(x), \nu_A(x)\rangle$, $A_1 = \langle \mu_{A_1}(x), \eta_{A_1}(x), \nu_{A_1}(x)\rangle$, and $A_2 = \langle \mu_{A_2}(x), \eta_{A_2}(x), \nu_{A_2}(x)\rangle$ with the help of the operator. Arithmetic operations between two different PF sets are performed as shown in the following equations.

$$A^c = \{\langle x, \nu_A(x), \eta_A(x), \mu_A(x)\rangle | x \in X\} \tag{3}$$

$$A_1 \oplus A_2 = \langle 1 - (1 - \mu_{A_1})(1 - \mu_{A_2}), \eta_{A_1}\eta_{A_2}, (\eta_{A_1} + \nu_{A_1})(\eta_{A_2} + \nu_{A_2}) - \eta_{A_1}\eta_{A_2}\rangle \tag{4}$$

$$A_1 \otimes A_2 = \langle (\mu_{A_1} + \eta_{A_1})(\mu_{A_2} + \eta_{A_2}) - \eta_{A_1}\eta_{A_2}, \eta_{A_1}\eta_{A_2}, 1 - (1 - \nu_{A_1})(1 - \nu_{A_2})\rangle \tag{5}$$

$$\lambda \cdot A = \langle 1 - (1 - \mu_A)^\lambda, (\eta_A)^\lambda, (\eta_A + \nu_A)^\lambda - (\eta_A)^\lambda\rangle \tag{6}$$

$$A^\lambda = \langle (\mu_A + \eta_A)^\lambda - (\eta_A)^\lambda, (\eta_A)^\lambda, 1 - (1 - \nu_A)^\lambda\rangle \tag{7}$$

The PF-weighted arithmetic mean operator (PFWAO) is calculated as shown in equation 8. where, $\langle \mu_{A_i}, \eta_{A_i}, \nu_{A_i}\rangle$ are the values of the picture fuzzy set. $\sum_{i=1}^{n} \lambda_i = 1$, $\lambda_i \in [0,1]$, and $i = 1, \dots, n$ and depending on the condition$\lambda_i = (\lambda_1, \dots, \lambda_n)^T$ denotes the weight vector of these values [27].

$$PFWAO_\lambda(A_1, \dots, A_n) = \bigoplus_{i=1}^{n} (\lambda_i, A_i) = \langle \begin{matrix} 1 - \prod_{i=1}^{n}(1 - \mu_{A_i})^{\lambda_i}, \prod_{i=1}^{n}(\eta_{A_i})^{\lambda_i}, \\ \prod_{i=1}^{n}(\eta_{A_i} + \nu_{A_i})^{\lambda_i} - \prod_{i=1}^{n}(\eta_{A_i})^{\lambda_i} \end{matrix} \rangle \tag{8}$$

The mathematical representation of the geometric mean operator PF is given in Eq.

$$9.PFWGO_\lambda(A_1, \dots, A_n) = \bigotimes_{i=1}^{n} (A_i)^{\lambda_i} =$$

$$\langle \prod_{i=1}^{n}(\mu_{A_i} + \eta_{A_i})^{\lambda_i} - \prod_{i=1}^{n}(\eta_{A_i})^{\lambda_i}, \prod_{i=1}^{n}(\eta_{A_i})^{\lambda_i}, 1 - \prod_{i=1}^{n}(1 - \nu_{A_i})^{\lambda_i}\rangle \tag{9}$$

Here, when A and B are considered as two different PF sets, an $X = \{x_1, x_2, \dots, x_n\}$. Hamming dh_P and the Euclidean(de_P) distance between both sets in space is given in equations 10 and 11 [8].

$$dh_P(A, B) = \frac{1}{n}\sum_{i=1}^{n}(|\mu_A(x_i) - \mu_B(x_i)| + |\eta_A(x_i) - \eta_B(x_i)| + |\nu_A(x_i) - \nu_B(x_i)|) \tag{10}$$

$$de_P(A, B) = \sqrt{\frac{1}{n}\sum_{i=1}^{n}[(\mu_A(x_i) - \mu_B(x_i))^2 + (\eta_A(x_i) - \eta_B(x_i))^2 + (\nu_A(x_i) - \nu_B(x_i))^2]} \tag{11}$$

After these processes, Eq. 12 is used for clarification. As a result of the clarification process, the fuzzy values are converted into clear numerical values (y). The set A given in the equation $A = \langle \mu_A, \eta_A, \nu_A \rangle$. The rejection rate is represented as $\pi = 1 - (\mu + \eta + \nu)$.

$$y = \left(\mu_A + \frac{\eta_A}{2}\right) + \frac{1+\left(\mu_A+\frac{\eta_A}{2}\right)-\left(\nu_A+\frac{\eta_A}{2}\right)}{2}\pi \tag{12}$$

After clarification, the score function for the PF set is defined as p=(μ,η,ν) as in eq. 13 [28].

$$S_{pxd}(p) = \mu - \nu + 1 + \frac{e^{\mu-\eta-\nu}}{1+\pi}, S_{pxd}(p) \in [e^{-1}, 2+e] \tag{13}$$

The following section shows the basic algorithm and implementation steps of the proposed integrated Entropy and MARCOS combination.

2.2 Picture fuzzy sets-based Entropy and MARCOS combination

PF set-based decision-making approaches, which are an extension of heuristic fuzzy sets, have n number of alternatives, $A_i = \{A_1, A_2, \ldots, A_m\}$, n number of criteria, $C_j = \{C_1, C_2, \ldots, C_n\}$ Accordingly, the weight transmitter, which expresses the characteristics of decision-makers with hesitation and abstention, is $w_k = \{w_1, w_2, \ldots, w_s\}$. It aims to evaluate by taking into account. The basic algorithm for the proposed model is presented in Figure 1.

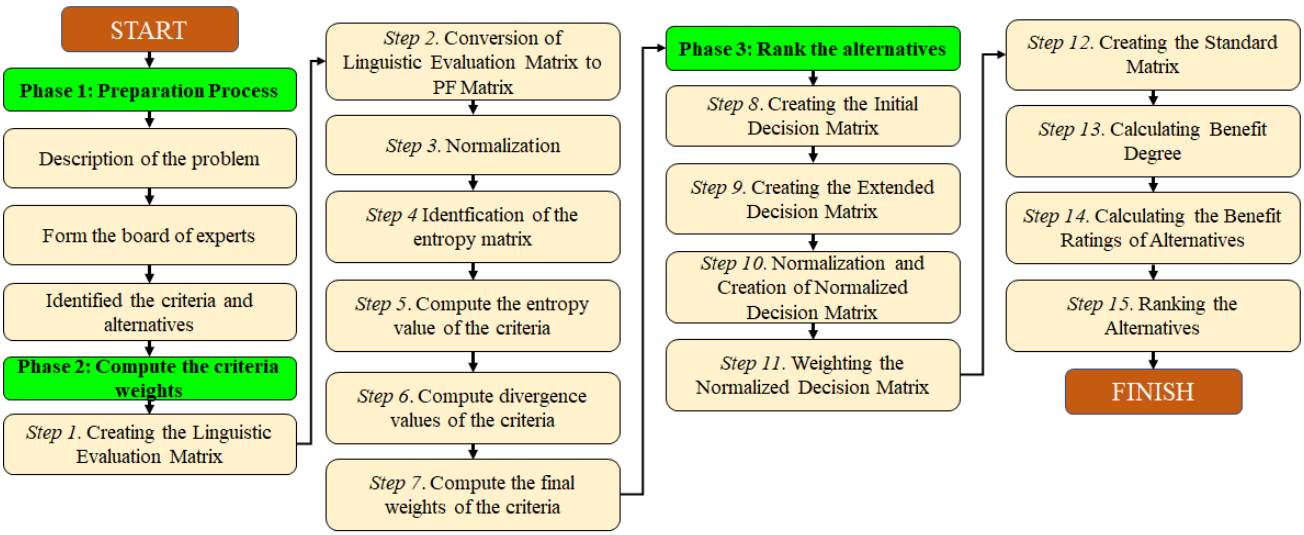

Fig. 1. The proposed PF Entropy – MARCOS combination and basic algorithm of the model

2.2.1 The Preparation Process

The preparation process consists of three sub-stages. In the first sub-stage, the problem is defined first. Then, a committee of experts is formed. For this, appraisers with complete expertise are selected from professionals with experience and extensive knowledge in the industry. In the last stage, the experts determine the criteria and alternatives for the evaluation process.

a) Description of the problem: The business climate has become increasingly competitive and intricate for small and medium-sized enterprises (SMEs), notably in the textile and apparel sector, and it forces these enterprises to focus on financial clarity, regulatory compliance, and operational efficiency to survive a highly competitive business environment. In this context, since independent accounting companies that produce and provide services in accounting, finance, and auditing play a critical role in managing financial reporting, tax liabilities, and strategic financial planning, which are challenging and complex activities, the selection of the most suitable independent accounting and

auditing firm as a strategic stakeholder provides textile enterprises with a strong and reliable instrument in coping with these difficulties. However, SMEs in the textile industry can often face significant challenges in making informed and objective decisions when choosing between multiple accounting and auditing service providers, as internal expertise is limited, uncertainties are highly complex and high, and expert judgments involve considerable subjectivity and bias.

Classical and traditional decision-making tools often fail to model and manage the ambiguities and hesitations that characterize assessments under real-life conditions in environments heavily influenced by multidimensional and complex uncertainties. Restrictions and structural problems of these frameworks can lead to suboptimal choices that jeopardize SMEs' financial efficiency and long-term sustainability capabilities in highly dynamic and changeable industries such as the textile industry. Furthermore, the textile sector's unique structure and needs are structured according to its requirements, and the lack of systematic and analytical tools further complicates decision processes.

To address these issues, this study proposes a robust and integrated multi-criteria decision-making (MCDM) framework that leverages Picture Fuzzy Sets (PFS), Entropy, and the MARCOS (Measurement of Alternatives and Ranking according to Compromise Solution) method. By incorporating degrees of membership, non-membership, and hesitancy, PFS provides a more realistic representation of expert opinions. The Entropy method offers objective criteria for weighting based on information distribution. At the same time, the MARCOS approach facilitates a systematic evaluation and ranking of alternatives concerning ideal and anti-ideal solutions. Together, these methods form a comprehensive decision-support model that guides SMEs in selecting the most appropriate accounting and auditing partners under uncertainty.

b) Construction of the board of experts: This study constructed an expert group that includes industry professionals with extensive knowledge and experience in different fields, as the proposed decision-making tool requires evaluations based on expert opinions. In selecting experts and forming the board, the dynamic and variable structure of the textile industry, the complex and uncertain practices of the accounting sector, and the contradictory criteria that should be considered in the decision-making process were considered. In this context, while selecting experts, fundamental factors such as professional experience, areas of expertise, and education were considered.

The researchers preferred experts with different graduation degrees, such as associate, bachelor's, master's, and Ph.D., in selecting specialists. This preference has allowed experts to include practical and theoretical knowledge in the evaluation process. In addition, the professionals selected for the board of experts come from different disciplines such as business, finance, accounting and auditing, industrial engineering, international trade, and logistics, thus providing a multifaceted perspective from various disciplines to evaluate accounting and auditing firms.

The professional experience of the members of the Board was also an essential criterion in the selection process. Specialists have experience ranging from 8 to 15 years, with a minimum of eight years. This way, getting opinions from people with theoretical knowledge and field experience was possible. In addition, the fact that each expert specializes in a particular field has increased the functionality of the Board. His expertise includes cost accounting, cash flow management, tax planning, ERP systems, payroll and social security incentives, and customs and VAT refund processes.

Another critical factor in forming the board of experts is that experts representing different sub-branches of the textile industry are included. Members of the Board: He works in various companies, such as medium-sized weaving companies for the domestic market, export-oriented large-scale apparel manufacturers, companies applying innovative textile technologies, SME-level home textile manufacturers, and labor-intensive workshops. Thanks to this structure, it has been ensured that the evaluations for the different types of companies served by accounting and auditing firms are more realistic and applicable. In conclusion, the expert panel involves specialists with interdisciplinary

knowledge who come from different experience levels and represent a wide range of the textile industry. This approach increased the reliability of the decision-making model developed in the study and strengthened the results' validity. Table 1 exhibits the members of the boards and their profiles.

Table 1
Experts and their profiles

Code	Degree	Field of Study	Experience	Type of Textile Company	Area of Expertise
E1	Bachelor's	Business Administration	12	Medium-sized domestic weaving firm	Cost Accounting
E2	Master's	Finance	9	Large-scale apparel manufacturer	Cash Flow Management
E3	Ph.D.	Accounting and Auditing	15	SME-level home textile producer	Tax Planning and Auditing
E4	Bachelor's	Industrial Engineering	8	Tech-integrated smart textile firm	ERP and Digital Accounting Systems
E5	Associate degree	Accounting and Tax Practices	11	Labor-intensive garment workshop	Payroll and Social Security Incentives
E6	Master's	International Trade and Logistics	10	Export-oriented denim manufacturer	Customs and VAT Refund Procedures

a) Identification of the criteria and alternatives: At this stage, the researchers determined the criteria by examining the previous literature studies and reviewing the relevant field's legal regulations and expert opinions. Table 2 shows the criteria identified. Top managers of the textile company determined alternatives, and they identified six independent accounting and auditing firms as options for the textile firm. Table 3 demonstrates the alternatives determined by the decision-makers.

Table 2
The criteria and definitions

Code	Criterion Name	Explanation	Type
C1	Sectoral Experience Period	Number of years the company has been operating in the textile industry	Benefit
C2	Service Cost (Monthly Average	Average monthly wage to be paid for SME	Cost
C3	Number of Expert Personnel	Number of accounting and auditing specialists within the company	Benefit
C4	Tax Incentive and Support Information	Level of knowledge of incentives and support specific to the textile industry	Benefit
C5	Location and Accessibility	Proximity and easy accessibility of the company to textile production centers	Benefit
C6	Use of Digital Applications and Automation	The level of digital accounting systems and automation infrastructure	Benefit
C7	Extra Service Fees	The cost of additional services such as payroll, incentive application	Cost
C8	Customer Satisfaction	Overall satisfaction level of current and former customers	Benefit
C9	Reporting Speed and Regularity	The degree to which reports are presented in a timely and regular manner	Benefit
C10	Regulatory Compliance and Up-to-Date	Legislative up-to-dateless and level of compliance in reporting and auditing	Benefit
C11	Communication Quality and Accessibility	Effectiveness and speed of communication with the customer	Benefit
C12	Contract Flexibility and Commitment Period	Flexibility of contracts and minimum length of service committed	Cost

Table 3
The alternatives

Code	Criterion Name
A1	M Auditing and Certified Public Accountants Inc.
A2	E Independent Auditing and Certified Public Accountants Inc.
A3	D Independent Auditing and Consulting Inc.
A4	A Istanbul International Auditing and Certified Public Accountants Inc.
A5	K Auditing and Certified Public Accountants Inc.
A6	V Auditing and Consulting Ltd. Co.

2.2.1 Identification of the Criteria Weights

At this stage, the application steps of the Entropy method are followed to determine the weights of the criteria. For this, experts evaluate each alternative with the help of the linguistic evaluation scale shown in Table 4, considering each criterion.

Table 4
PF Linguistic appraisal scale

Linguistic terms	Abbreviations	$(\mu; I; \nu)$	Linguistic terms	Abbreviations	$(\mu; I; \nu)$
Extremely low	EL	(0,0,1)	Above middle	AM	(0.6,0.2,0.2)
Very low	VL	(0.1,0.3,0.6)	Middle high	MH	(0.7,0.1,0.1)
Low	L	(0.2,0.3,0.5)	High	H	(0.8,0.1,0.1)
Middle low	ML	(0.3,0.3,0.3)	Very high	VH	(0.9,0,0.1)
Below middle	BM	(0.4,0.2,0.3)	Extremely high	EH	(1,0,0)
Middle	M	(0.5,0.2,0.2)			

Step 1. Creation of Linguistic Evaluation Matrix: In this step, the first linguistic decision matrices, consisting of the linguistic evaluations of the decision makers, are created. At the end of this process, a linguistic decision matrix is obtained for as many decision-makers as possible.

Step 2. Conversion of Linguistic Assessment Matrix to Picture Fuzzy (PF) Matrix: In this step, decision-makers' qualitative (verbal) assessments are translated into numerical values per the predetermined linguistic assessment scale. Picture fuzzy values corresponding to linguistic expressions (e.g., "perfect," "medium," "poor") are matched in line with this scale to obtain a PF evaluation matrix for each decision maker. This transformation process makes expert opinions more measurable and comparable within the fuzzy logic framework. After the evaluations are converted into numerical form, the evaluation matrices of multiple decision-makers are combined to reach a single collective evaluation matrix. This joining process is carried out with the help of the mathematical operator indicated in the study, shown in equation nine. Thus, the average evaluation score of each alternative according to each criterion is calculated in a picture fuzzy structure to reflect the common opinion of the decision-makers. This method creates a more balanced and reliable ground for decision support by considering individual differences. Besides, the PF matrices are aggregated by employing the PF-weighted arithmetic mean operator (PFWAO) given in Eq. (9).

Step 3. Identification of the Hamming dh_P and the Euclidean(de_P) distance: In this step, the Hamming $\mathrm{dh_P}$ and the Euclidean$(\mathrm{de_P})$ distances are determined with the help of Eqs. (10) and (11).

Step 4. Defuzzification of the PF numbers to crisp values: In this step, the PF numbers of the matrix are defuzzified, and the crisp values are obtained by using Eq. (12). Then, the score functions are calculated with the help of Eq. (13) to obtain the initial decision matrix. Afterward, the implementation steps of the Entropy method are followed.

Step 5. Implementation of the Entropy technique: In the fifth step of the suggested model, the basic algorithm of the entropy method, an objective weighting approach, is followed.

Step 5.1 Generation of the initial decision matrix: In the first step of the entropy method, the initial decision matrix is constructed using the obtained score functions computed in the previous step.

Step 5.2 Normalization of the initial decision matrix: Each element is normalized by employing Eq. (14).

$$r_{ij} = \frac{x_{ij}}{\sum_{i=1}^{m} x_{ij}} \tag{14}$$

Step 5.3 Computing the entropy value of each element: The entropy value of each element of the normalized matrix is computed by employing Eq. (15).

$$e_{ij} = r_{ij}.\left((ln)r_{ij}\right) \tag{15}$$

Then, the entropy matrix is generated using these values, as shown in Eq. (16).

$$E = \begin{bmatrix} e_{11}\ e_{12} \dots e_{1k} \dots e_{1K} \\ e_{21}\ e_{22} \dots e_{2k} \dots e_{2K} \\ .\ \ .\ \ .\ \ .\ \ .\ \ . \\ e_{i1}\ e_{i2} \dots e_{ik} \dots e_{iK} \\ .\ \ .\ \ .\ \ .\ \ .\ \ . \\ e_{l1}\ e_{l2}\ .\ e_{lk}\ .\ e_{lK} \end{bmatrix} \tag{16}$$

Step 5.4 Computing the final entropy, divergence, and weight values of each criterion: Here, the final entropy, divergence, and weight values of each criterion are calculated by employing Eqs. (17), (18), and (19).

$$\varepsilon_{ij} = \left(\frac{-1}{\ln(m)}\right).\sum_{i=1}^{m}\left[r_{ij}.\left((ln)r_{ij}\right)\right]; \forall j \tag{17}$$

After calculating the entropy values, the divergence value (d_{ij}) is computed with the help of Eq. (18).

$$d_{ij} = 1 - \varepsilon_{ij}; \forall j \tag{18}$$

Finally, the weight of each criterion is identified by employing Eq. (19).

$$w_j = \frac{d_{ij}}{\sum_{i=1}^{m} d_{ij}}; \forall j \tag{19}$$

Step 6. Evaluation of alternatives ranking performances: In this stage of the algorithm, the alternatives' ranking performances are assessed with the MARCOS approach. The implementation steps for the proposed method are exhibited below [24].

Step 6.1 Construction of the initial decision matrix: In this process, the first decision matrix is used in the first stage of the entropy method.

Step 6.2 Creation of the extended decision matrix: In this process, an extended decision matrix is created by adding ideal and anti-ideal values to the initial decision matrix according to the directions of the criteria.

Step 6.3 Normalization and creation of normalized decision matrix: In the tenth step, it is standardized using Eq. (20).

$$n_{ij} = \begin{cases} \dfrac{x_{ij} - x_{ij}^{\min}}{x_{ij}^{\max} - x_{ij}^{\min}} & j \in B \\ \dfrac{x_{ij}^{\max} - x_{ij}}{x_{ij}^{\max} - x_{ij}^{\min}} & j \in C \end{cases} \tag{20}$$

Step 6.4 Weighting of the Normalized Decision Matrix: The normalized decision matrix elements obtained in this step are weighed with the help of the weight values obtained in the Entropy method. For this, Eq. (21) is used.

$$\xi_{ij} = n_{ij}.w_j \tag{21}$$

Step 6.5 Calculation of the degree of utility of alternatives: Using Eqs. (22) and (23), each alternative's utility degree is calculated.

$$\varphi_i^- = \frac{s_i}{s_{aai}} \tag{22}$$

$$\varphi_i^+ = \frac{s_i}{s_{ai}} \tag{23}$$

Then, with the help of Eq. (21), the matrix S is created. The S value refers to the sum of the element values of the normalized weighted matrix.

$$S_i = \sum_{i=1}^{n} \xi_{ij} \tag{24}$$

Step 6.6 Calculation of utility functions of alternatives: With the help of Eq. (25), the utility function value of each alternative is calculated.

$$f\left(\varphi_i\right) = \frac{\varphi_i^+ + \varphi_i^-}{1 + \dfrac{1 - f\left(\varphi_i^+\right)}{f\left(\varphi_i^+\right)} + \dfrac{1 - f\left(\varphi_i^-\right)}{f\left(\varphi_i^-\right)}} \tag{25}$$

Where, $f(K_i^+)$ while defining the utility functions related to the proximity of alternatives to ideal solutions, it expresses their distance from anti-ideal solutions. Then, the utility function for both ideal and anti-ideal solutions is calculated with the help of the following equations.

$$f\left(\varphi_i^+\right) = \frac{\varphi_i^-}{\varphi_i^+ + \varphi_i^-} \tag{26}$$

$$f\left(\varphi_i^-\right)=\frac{\varphi_i^+}{\varphi_i^++\varphi_i^-} \tag{27}$$

Step 6.7 Ranking of Alternatives: In the last application step, the alternatives are listed by considering the benefit function of the alternatives.

2. A Numerical Illustration

In this section, the decision-making model given above and the implementation steps and basic algorithm are applied to the decision-making problem of choosing the appropriate independent accounting firm with which a medium-sized textile company will cooperate as a long-term strategic alliance to provide accounting, auditing, and reporting services. The preparation process was completed as described in the previous section. The research problems were defined, then the committee of experts was formed, the criteria and alternatives were determined, and the implementation steps of the model were started.

Steps 1-2. In the first implementation step, decision-makers given in Table 1 performed linguistic evaluations with the help of a linguistic evaluation scale for each alternative, considering the criteria. Table 3 shows the PF values of the linguistic assessment scale. The experts' linguistic assessments are given in Appendix Table A. After the linguistic evaluations were collected, they were converted into pictorial fuzzy values on the linguistic evaluation scale according to these evaluations. With the help of Eq. (9), these evaluations are combined. Table 5 shows the consolidated PF decision matrix.

Step 3. Then, the combined decision matrix is normalized with the help of Eqs. (10) and (11). The normalized PF decision matrix is shown in Table 6.

Table 5
Integrated decision matrix

	C1			C2			C3			C4			C5			C6		
	m	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*
A1	0.700	0.100	0.100	0.569	0.200	0.200	0.600	0.200	0.200	0.613	0.151	0.151	0.500	0.200	0.200	0.569	0.200	0.200
A2	0.449	0.218	0.287	0.647	0.137	0.184	0.300	0.300	0.300	0.459	0.218	0.260	0.500	0.200	0.200	0.569	0.200	0.200
A3	0.539	0.239	0.239	0.585	0.200	0.200	0.786	0.100	0.100	0.500	0.200	0.200	0.571	0.184	0.184	0.619	0.184	0.184
A4	0.626	0.206	0.206	0.600	0.200	0.200	0.571	0.184	0.184	0.786	0.100	0.100	0.594	0.168	0.168	0.619	0.184	0.184
A5	0.700	0.100	0.100	0.300	0.300	0.300	0.900	0.000	0.100	0.733	0.117	0.117	0.500	0.200	0.200	0.619	0.184	0.184
A6	1.000	0.000	0.000	0.551	0.225	0.392	1.000	0.000	0.000	1.000	0.000	0.051	0.900	0.000	0.100	1.000	0.000	0.051

Table 5
Continued

	C7			C8			C9			C10			C11			C12		
	m	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*
A1	0.600	0.200	0.200	0.500	0.200	0.200	0.500	0.200	0.200	0.578	0.168	0.168	0.500	0.200	0.200	0.338	0.284	0.284
A2	0.720	0.100	0.100	0.500	0.200	0.200	0.500	0.200	0.200	0.500	0.200	0.200	0.500	0.200	0.200	0.521	0.240	0.254
A3	0.600	0.200	0.200	0.500	0.200	0.200	0.536	0.200	0.200	0.500	0.200	0.200	0.541	0.184	0.184	0.323	0.284	0.323
A4	0.544	0.218	0.218	0.571	0.184	0.184	0.536	0.200	0.200	0.684	0.151	0.151	0.500	0.200	0.200	0.294	0.284	0.384
A5	0.536	0.200	0.200	0.500	0.200	0.200	0.536	0.200	0.200	0.632	0.168	0.168	0.571	0.184	0.184	0.300	0.300	0.300
A6	0.295	0.268	0.428	0.900	0.000	0.100	1.000	0.000	0.068	1.000	0.000	0.051	0.900	0.000	0.100	0.190	0.257	1.000

Table 6
Normalized decision matrix

	C1			C2			C3			C4			C5			C6		
	m	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*
A1	0.700	0.100	0.100	0.200	0.200	0.569	0.600	0.200	0.200	0.613	0.151	0.151	0.500	0.200	0.200	0.569	0.200	0.200
A2	0.449	0.218	0.287	0.184	0.137	0.647	0.300	0.300	0.300	0.459	0.218	0.260	0.500	0.200	0.200	0.569	0.200	0.200
A3	0.539	0.239	0.239	0.200	0.200	0.585	0.786	0.100	0.100	0.500	0.200	0.200	0.571	0.184	0.184	0.619	0.184	0.184

A4	0.626	0.206	0.206	0.200	0.200	0.600	0.571	0.184	0.184	0.786	0.100	0.100	0.594	0.168	0.168	0.619	0.184	0.184
A5	0.700	0.100	0.100	0.300	0.300	0.300	0.900	0.000	0.100	0.733	0.117	0.117	0.500	0.200	0.200	0.619	0.184	0.184
A6	1.000	0.000	0.000	0.392	0.225	0.551	1.000	0.000	0.000	1.000	0.000	0.051	0.900	0.000	0.100	1.000	0.000	0.051

Table 6
Continued

	C7			C8			C9			C10			C11			C12		
	m	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*	*m*	*e*	*v*
A1	0.200	0.200	0.600	0.200	0.200	0.500	0.200	0.200	0.500	0.578	0.168	0.168	0.500	0.200	0.200	0.338	0.284	0.284
A2	0.100	0.100	0.720	0.200	0.200	0.500	0.200	0.200	0.500	0.500	0.200	0.200	0.500	0.200	0.200	0.521	0.240	0.254
A3	0.200	0.200	0.600	0.200	0.200	0.500	0.200	0.200	0.536	0.500	0.200	0.200	0.541	0.184	0.184	0.323	0.284	0.323
A4	0.218	0.218	0.544	0.184	0.184	0.571	0.200	0.200	0.536	0.684	0.151	0.151	0.500	0.200	0.200	0.294	0.284	0.384
A5	0.200	0.200	0.536	0.200	0.200	0.500	0.200	0.200	0.536	0.632	0.168	0.168	0.571	0.184	0.184	0.300	0.300	0.300
A6	0.428	0.268	0.295	0.100	0.000	0.900	0.068	0.000	1.000	1.000	0.000	0.051	0.900	0.000	0.100	0.190	0.257	1.000

Step 4. Then, considering the normalized PF matrix values, pictorial fuzzy values are clarified with the help of Eq. (12). Then, using Eq. (13), the score function values are determined. Table 7 shows the score function values obtained after normalization.

Table 7
Score function values

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	3.0988	1.1800	2.6214	2.7183	2.3047	2.5179	1.1488	1.2514	1.2514	2.5839	2.3047	1.7804
A2	2.0644	1.0691	1.6735	2.1225	2.3047	2.5179	0.8311	1.2514	1.2514	2.3047	2.3047	2.3119
A3	2.3813	1.1640	3.4581	2.3047	2.5409	2.7027	1.1488	1.2514	1.2141	2.3047	2.4459	1.7039
A4	2.7067	1.1488	2.5409	3.4581	2.6346	2.7027	1.2419	1.1460	1.2141	2.9766	2.3047	1.5740
A5	3.0988	1.6735	4.0255	3.2111	2.3047	2.7027	1.2141	1.2514	1.2141	2.7654	2.5409	1.6735
A6	4.7183	1.6591	4.7183	4.6707	4.0255	4.6707	1.9992	0.6493	0.4902	4.6707	4.0255	0.8124

Step 5. In this step, the implementation steps of the entropy method are followed.

Step 5.1. The initial decision matrix was constructed using the obtained score functions computed in the previous step. Table 7 demonstrates the initial decision matrix.

Step 5.2. Then, the initial decision matrix elements were normalized using Eq. (14). The normalized matrix is presented in Table 8.

Table 8
The normalized matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	0.1715	0.1495	0.1377	0.1471	0.1430	0.1413	0.1515	0.1840	0.1886	0.1468	0.1447	0.1806
A2	0.1143	0.1354	0.0879	0.1148	0.1430	0.1413	0.1096	0.1840	0.1886	0.1309	0.1447	0.2346
A3	0.1318	0.1474	0.1816	0.1247	0.1577	0.1517	0.1515	0.1840	0.1830	0.1309	0.1536	0.1729
A4	0.1498	0.1455	0.1335	0.1871	0.1635	0.1517	0.1638	0.1685	0.1830	0.1691	0.1447	0.1597
A5	0.1715	0.2120	0.2115	0.1737	0.1430	0.1517	0.1601	0.1840	0.1830	0.1571	0.1595	0.1698
A6	0.2611	0.2102	0.2478	0.2527	0.2498	0.2622	0.2636	0.0955	0.0739	0.2653	0.2528	0.0824

Steps 5.3-5.4. The Entropy value of each element of the initial decision matrix was computed by employing Eq. (15), and the entropy matrix was constructed as shown in Table 9. Next, each criterion's final entropy, divergence, and weight values are calculated by employing Eqs. (17), (18), and (19).

Table 9
The entropy matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	-0.3024	-0.2841	-0.2730	-0.2819	-0.2781	-0.2765	-0.2859	-0.3115	-0.3146	-0.2816	-0.2797	-0.3091
A2	-0.2479	-0.2708	-0.2137	-0.2485	-0.2781	-0.2765	-0.2423	-0.3115	-0.3146	-0.2662	-0.2797	-0.3401
A3	-0.2671	-0.2823	-0.3098	-0.2596	-0.2913	-0.2861	-0.2859	-0.3115	-0.3108	-0.2662	-0.2877	-0.3034
A4	-0.2844	-0.2805	-0.2688	-0.3136	-0.2961	-0.2861	-0.2963	-0.3001	-0.3108	-0.3005	-0.2797	-0.2930
A5	-0.3024	-0.3288	-0.3285	-0.3041	-0.2781	-0.2861	-0.2933	-0.3115	-0.3108	-0.2907	-0.2928	-0.3011
A6	-0.3506	-0.3278	-0.3457	-0.3476	-0.3465	-0.3510	-0.3515	-0.2243	-0.1925	-0.3520	-0.3476	-0.2057
ε_{ij}	0.9793	0.9902	0.9709	0.9796	0.9869	0.9836	0.9796	0.9880	0.9789	0.9807	0.9864	0.9781
d_{ij}	0.0207	0.0098	0.0291	0.0204	0.0131	0.0164	0.0204	0.0120	0.0211	0.0193	0.0136	0.0219
w_j	0.0949	0.0449	0.1335	0.0936	0.0603	0.0753	0.0939	0.0551	0.0968	0.0885	0.0625	0.1008

As shown in Table 9, the C3 "Number of Expert Personnel" criterion, which is defined as the number of accounting and auditing experts within the company, has been determined as the most effective criterion. C12 follows it, "Contract Flexibility and Commitment Period," and C9, "Reporting Speed and Regularity," respectively. Other criteria are listed as C1 "Duration of Sectoral Experience">, C7 "Extra Service Fees"> C4 "Tax Incentive and Support Information"> C10 "Compliance and Up-to-dateness >" C6 "Use of Digital Application and Automation,"> C11 "Communication Quality and Accessibility,"> C5 "Location and Accessibility,"> C8 "Customer Satisfaction" > C2 "Service Cost."

Step 6. In the following phase, the MARCOS approach was implemented to identify the ranking performance of the alternatives.

Step 6.1. In this implementation step, we used the same initial decision matrix, and to avoid repetition, we did not show this matrix here for the second time.

Step 6.2. In this process, an extended decision matrix was created by adding ideal and anti-ideal values to the initial decision matrix according to the directions of the criteria.

Step 6.3. In this step, the elements of the extended decision matrix were normalized using Eq. (20). The extended decision matrix is presented in Table 10.

Table 10
The extended and normalized decision matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
AAI	0.4375	0.6388	0.3547	0.4544	0.5725	0.5391	0.4157	0.5189	0.3917	0.4934	0.5725	0.3514
A1	0.6568	0.9060	0.5556	0.5820	0.5725	0.5391	0.7234	1.0000	1.0000	0.5532	0.5725	0.4563
A2	0.4375	1.0000	0.3547	0.4544	0.5725	0.5391	1.0000	1.0000	1.0000	0.4934	0.5725	0.3514
A3	0.5047	0.9184	0.7329	0.4934	0.6312	0.5787	0.7234	1.0000	0.9702	0.4934	0.6076	0.4768
A4	0.5737	0.9306	0.5385	0.7404	0.6545	0.5787	0.6692	0.9157	0.9702	0.6373	0.5725	0.5162
A5	0.6568	0.6388	0.8532	0.6875	0.5725	0.5787	0.6846	1.0000	0.9702	0.5921	0.6312	0.4855
A6	1.0000	0.6444	1.0000	1.0000	1.0000	1.0000	0.4157	0.5189	0.3917	1.0000	1.0000	1.0000
AI	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000

Step 6.4. In this step, the elements of the normalized matrix are weighed with the help of Eq. (21). Table 11 shows the weighted normalized matrix.

Table 11
The weighted normalized matrix

	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	SAAI
AAI	0.0415	0.0287	0.0474	0.0426	0.0345	0.0406	0.0390	0.0286	0.0379	0.0436	0.0358	0.0354	0.4556
A1	0.0623	0.0407	0.0742	0.0545	0.0345	0.0406	0.0679	0.0551	0.0968	0.0489	0.0358	0.0460	0.6573
A2	0.0415	0.0449	0.0474	0.0426	0.0345	0.0406	0.0939	0.0551	0.0968	0.0436	0.0358	0.0354	0.6120
A3	0.0479	0.0412	0.0979	0.0462	0.0380	0.0436	0.0679	0.0551	0.0939	0.0436	0.0380	0.0480	0.6614
A4	0.0544	0.0418	0.0719	0.0693	0.0394	0.0436	0.0628	0.0504	0.0939	0.0564	0.0358	0.0520	0.6718
A5	0.0623	0.0287	0.1139	0.0644	0.0345	0.0436	0.0643	0.0551	0.0939	0.0524	0.0395	0.0489	0.7014
A6	0.0949	0.0289	0.1335	0.0936	0.0603	0.0753	0.0390	0.0286	0.0379	0.0885	0.0625	0.1008	0.8438
AI	0.0949	0.0449	0.1335	0.0936	0.0603	0.0753	0.0939	0.0551	0.0968	0.0885	0.0625	0.1008	1.0000
SAI	0.4997	0.2996	0.7198	0.5068	0.3361	0.4033	0.5287	0.3830	0.6479	0.4655	0.3456	0.4673	

Steps 6.5, 6.6, and 6.7. Using equations 22 and 23, the degree of utility of each alternative was calculated. Then, using eq. 24, respectively, S_i values and utility function values of the alternatives are calculated. Finally, in the last step, alternatives are asked for by considering the utility functions. Table 12. Degrees of the utility of alternatives S_i. It shows the values as well as the benefit functions with its values.

Table 12
The final results

	S_i						
AAI	0.455571889	K_i^-	K_i^+	$f(K_i^-)$	$f(K_i^+)$	$f(K_i)$	Rank
A1	0.657257339	1.44271	0.65726	0.31298	0.68702	0.57524	5
A2	0.612003101	1.34337	0.61200	0.31298	0.68702	0.53563	6
A3	0.661376848	1.45175	0.66138	0.31298	0.68702	0.57884	4
A4	0.671792109	1.47461	0.67179	0.31298	0.68702	0.58796	3
A5	0.701377013	1.53955	0.70138	0.31298	0.68702	0.61385	2
A6	0.843817163	1.85222	0.84382	0.31298	0.68702	0.73851	1
AI	1						

As shown in Table 12, the highest-ranking performance was shown by A6 "V Auditing and Consulting Ltd. Co.". A5 K Auditing and Certified Public Accountants Inc. and A4 A Istanbul International Auditing and Certified Public Accountants Inc. follow it. Other accounting firms received different ranking scores, > A3 D Independent Auditing and Consulting Inc. > A1 M Auditing and Certified Public Accountants Inc. A2 E Independent Auditing and Certified Public Accountants Inc.

3. Robustness and Validity Check

This study conducted a series of analyses to test the validity and robustness of the proposed PF-ENTROPY & MARCOS integrated model. First, the effects of possible changes in the criteria weights on the ranking results were examined. For this purpose, the algorithm proposed by Görçün et al. [29] was followed, and the criteria were ranked according to their original relative importance values determined during the weighting process. Starting with the most influential criterion, its weight was reduced by 10% in the first scenario. Then, this reduction was continued gradually until the weight of the same criterion reached zero. Simultaneously, in each scenario, the amount reduced from the criterion was equally distributed among the remaining criteria, ensuring that the total sum of the criteria weights remained equal to one. This process was repeated for all criteria down to the least influential one. Accordingly, ten scenarios were created for each criterion, resulting in 120 scenarios. For each scenario, calculations were repeated based on the modified criterion weights, and it was observed whether there was any change in the ranking performance of the alternatives. Figure 2

presents the new ranking results obtained for the 120 scenarios based on the altered criterion weights.

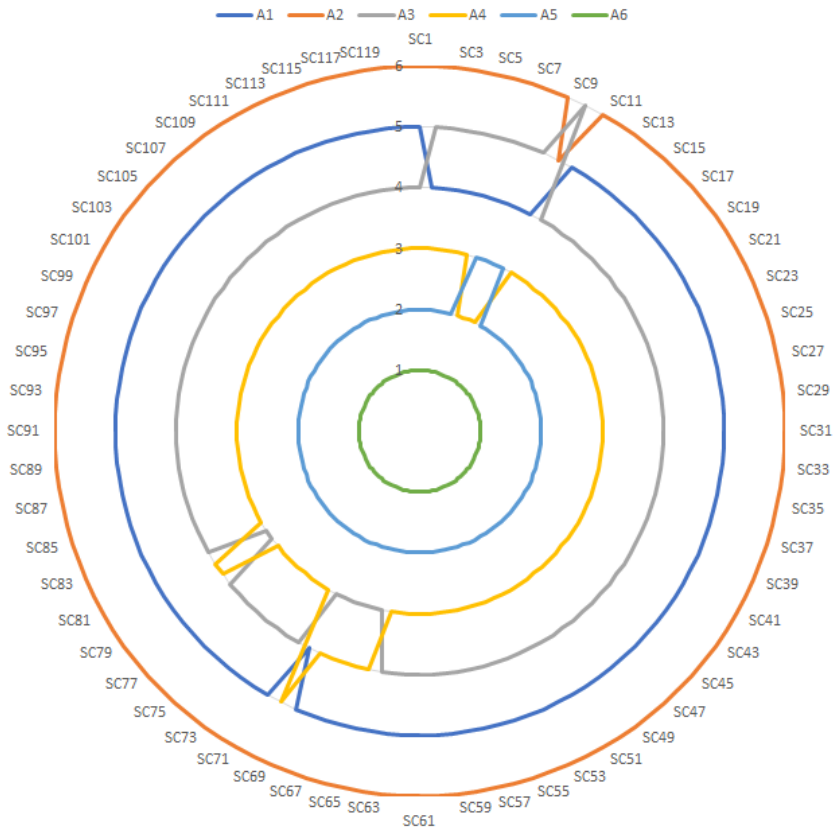

Fig. 2. The new ranking results for the changing criteria weights

As shown in Figure 2, no change occurred in the ranking results for the most suitable accounting firm across 120 scenarios, and the A6 alternative maintained its position in the ranking. The second-best alternative, A5, dropped in the ranking in four scenarios; when the weight of the C3 criterion was reduced by 70% or more, A5's ranking performance declined. The ranking performance of A2 changed in only one scenario, and this occurred when the value of the C3 criterion was entirely reduced to zero.

In addition, when the original results were compared with those obtained from 120 scenarios, the average similarity ratio reached a remarkably high value of 0.939. In the literature, some researchers [30,31] consider a similarity ratio of 70% and above to be reasonable, while Saaty [32] and Belton & Stewart [33] argued that a value of 85% and above is acceptable. However, the average similarity ratio obtained in this study exceeded the value suggested by Saaty [32] and Belton & Stewart [33], thereby demonstrating that the proposed model is highly robust, consistent, and reliable.

In the second phase of the analysis, the robustness of the proposed decision-making tool against the rank reversal problem—a critical limitation and structural issue in decision-making tools—was examined. For this purpose, in each scenario, the worst alternative was eliminated, and calculations were repeated for the remaining alternatives, after which it was evaluated whether any differences occurred in the ranking results. Figure 3 shows the proposed model's robustness against the rank reversal problem.

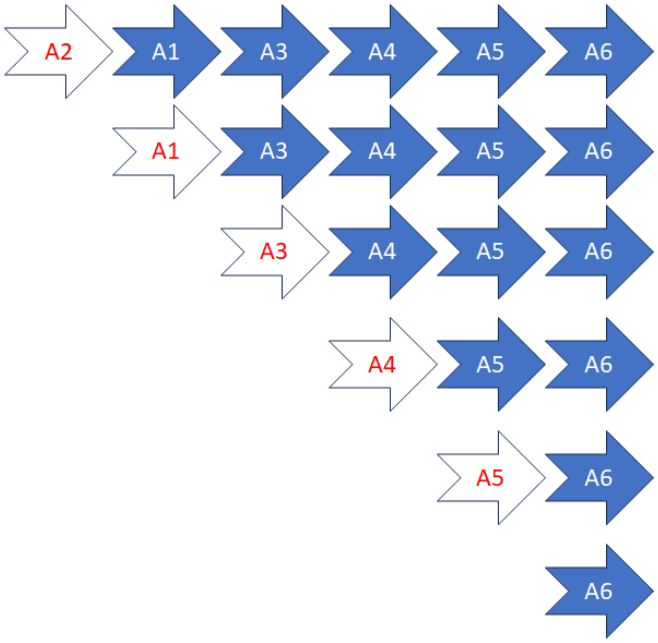

Fig. 3. The resistance of the suggested model

As shown in Figure 3, the alternatives maintained their respective rankings in each scenario. This situation proves that the proposed methodology is robust and reliable.

3. Results

In today's highly volatile and competitive business environment, small and medium-sized enterprises (SMEs)—especially in the textile sector—face increasing pressure to ensure financial transparency, comply with complex regulatory frameworks, and maintain strategic cost-effectiveness. The selection of appropriate accounting and auditing service providers plays a pivotal role in addressing these challenges. However, this selection process is often characterized by multidimensional uncertainty, information asymmetry, and subjective expert judgments, which render traditional decision-making tools insufficient. The present study introduces and applies a novel multi-criteria decision-making (MCDM) framework that integrates Picture Fuzzy Sets (PFS), Entropy, and the MARCOS method to evaluate and rank six accounting and auditing firms specifically for textile SMEs.

The decision-making model was structured around 12 evaluation criteria, encompassing qualitative and quantitative service quality dimensions, financial implications, digital capabilities, contractual flexibility, and compliance. The criteria were weighted using the entropy method—an objective approach that quantifies the informational contribution of each criterion—while expert evaluations were captured using PFS to handle hesitancy, neutrality, and ambiguity. Finally, the MARCOS method was employed to derive each alternative's relative utility and final ranking.

The entropy-based analysis revealed that the "Number of Expert Personnel" (C3) emerged as the most influential criterion in the decision-making process. It indicates that SMEs emphasize service providers' technical and human resource capacity, possibly due to the complexity of textile financial practices and sector-specific requirements. The following most impactful criteria were "Contract Flexibility and Commitment Period" (C12) and "Reporting Speed and Regularity" (C9), underscoring the value of adaptable service models and timely financial reporting in maintaining operational agility and fiscal responsibility.

On the contrary, "Service Cost" (C2) and "Customer Satisfaction" (C8) were found to be the least weighted criteria. This finding suggests that while cost considerations are relevant, SMEs may

prioritize competence, responsiveness, and regulatory compliance over cost minimization alone—especially in a sector where errors in financial handling can result in severe penalties and strategic misalignments.

The MARCOS-based evaluation demonstrated that A6 (V Auditing and Consulting Ltd. Co.) was the most suitable service provider, achieving the highest utility score of 0.8438. This firm was a firm in digital integration (C6), staff expertise (C3), and regulatory compliance (C10), positioning itself as a strategic partner for SMEs aiming to transform and future-proof their operations digitally. Following A6, A5 (K Auditing and Certified Public Accountants Inc.) and A4 (A Istanbul International Auditing and Certified Public Accountants Inc.) ranked second and third, respectively. These alternatives performed consistently well across the most impactful criteria but showed lower utility scores in contractual flexibility or digital systems, which may have limited their final rankings.

Conversely, A2 (E Independent Auditing and Certified Public Accountants Inc.) received the lowest utility score (0.6120), reflecting its comparative deficiencies in several critical areas, including reporting regularity and staff capacity. Interestingly, A1 (M Auditing and Certified Public Accountants Inc.) and A3 (D Independent Auditing and Consulting Inc.) held intermediate positions, indicating moderate performance across most criteria but lacking standout strengths.

The robustness of the proposed model was tested through a comprehensive sensitivity analysis involving 120 scenarios where criterion weights were systematically altered. The results showed remarkable stability in rankings, particularly for A6, whose position remained unchanged across all scenarios. A5 experienced minor shifts in four scenarios, predominantly when the weight of C3 was reduced by 70% or more. Furthermore, the model achieved an average similarity index of 0.939, far exceeding the commonly accepted thresholds for model robustness (typically ≥0.85).

The model's resistance to the rank reversal problem—a common vulnerability in MCDM tools—was also verified. Successive removal of the lowest-ranked alternatives and recalculation of rankings confirmed the internal consistency and structural integrity of the PF-Entropy-MARCOS framework. This validation supports the model's application in the textile sector and other industry contexts characterized by uncertainty and multidimensional evaluation needs.

The findings of this study offer several important managerial implications for decision-makers in textile SMEs, as well as for policymakers aiming to support financial transparency and sustainable growth within the SME ecosystem.

From a managerial standpoint, the research emphasizes that SMEs must adopt a more strategic, data-informed approach when selecting accounting and auditing partners. The integrated Picture Fuzzy Entropy–MARCOS model offers an evidence-based decision-support system that can significantly improve decision quality under uncertainty—prioritizing criteria such as "Number of Expert Personnel" and "Reporting Speed and Regularity" signals to SME managers that technical capacity and timely service delivery are more consequential than merely minimizing costs.

This insight challenges the conventional wisdom among smaller enterprises that lower fees should be a primary selection driver. Instead, decision-makers should shift focus toward capability alignment, particularly in contexts where financial mismanagement or reporting delays can have regulatory or reputational consequences. Moreover, the critical weight assigned to "Contract Flexibility" suggests that SMEs increasingly value adaptable service agreements that allow them to scale or reorient their operations without being locked into rigid contractual structures.

For operational managers, the preference for firms with advanced digital systems (C6) highlights a growing digitalization imperative. The accounting and auditing firm's integration of ERP systems, automated reporting tools, and cloud-based platforms may offer both efficiency gains and better data integrity, faster decision cycles, and regulatory compliance.

At the policy level, the results signal a need for institutional support mechanisms that help SMEs access and evaluate service providers more objectively. Policymakers could promote the development of sector-specific MCDM frameworks like the one proposed here to guide SME procurement and partnership decisions in accounting, auditing, and beyond.

Furthermore, the relatively low weight of "Customer Satisfaction" (C8) in expert evaluations could imply information asymmetry or a lack of transparent public reviews in the professional service sector. Policymakers and trade associations may address this by encouraging standardized, publicly accessible performance benchmarks and satisfaction indices for certified public accountants and auditors.

Another important implication involves capacity-building initiatives. Since the "Number of Expert Personnel" was deemed the most critical factor, regulatory bodies, and professional associations may consider developing certification and continuous training programs to expand the qualified labor pool in accounting and auditing, particularly regarding textile industry expertise. It, in turn, could improve service quality and alignment with sector-specific needs.

The strategic insights arising from this study extend beyond the textile sector. First, the robustness of the decision-support framework and its resilience to weight and rank reversals underscore its potential applicability in other sectors marked by uncertainty, regulation, and intense competition, such as logistics, pharmaceuticals, or renewable energy.

Second, the study reflects a deeper trend in SME ecosystems: the professionalization of supplier selection processes. Rather than relying on informal networks or anecdotal references, SMEs gradually embrace structured, data-driven tools to manage strategic partnerships—a signal of organizational maturity.

Finally, the integration of Picture Fuzzy Sets demonstrates how linguistic uncertainty and cognitive hesitation can be mathematically operationalized, offering researchers and practitioners a sophisticated yet accessible tool to bridge the gap between subjective expertise and objective decision-making.

In conclusion, the integrated PF-Entropy and MARCOS-based decision-support model developed in this study offers a systematic, objective, and adaptable framework for SME managers when selecting accounting and auditing service providers. By enhancing decision quality and addressing uncertainty with methodological rigor, the model delivers valuable contributions at both managerial and policy levels. Its proven robustness and flexibility make it applicable beyond the textile industry, serving as a transferable tool for other sectors facing similar complexity and decision-making challenges. Ultimately, this framework is a strategic reference for organizations seeking to make more transparent, consistent, and forward-looking decisions in uncertain and dynamic environments.

4. Conclusions

This study proposed a robust, flexible, and structured multi-criteria decision-making (MCDM) framework that integrates Picture Fuzzy Sets (PFS), the Entropy method, and the MARCOS approach to support the selection of suitable accounting and auditing firms for SMEs in the textile industry. In environments characterized by high levels of uncertainty, such as the textile sector, traditional decision-making methods often fall short due to their inability to accommodate expert hesitation and ambiguous judgments. The proposed model effectively overcomes these limitations by combining linguistic assessments with quantitative rigor and enables decision-makers to rank alternatives more accurately based on subjective and objective criteria.

The empirical application confirmed the model's practical utility and decision-making power. Among the twelve criteria evaluated, "Number of Expert Personnel," "Contract Flexibility and

Commitment Period," and "Reporting Speed and Regularity" emerged as the most influential, indicating that technical capacity, responsiveness, and adaptable contracts are key priorities for SMEs. The alternative A6 (V Auditing and Consulting Ltd. Co.) was identified as the most appropriate service provider, offering superior performance across critical evaluation dimensions. Furthermore, robustness and sensitivity analyses demonstrated the model's resilience to weight variations and rank reversals, reinforcing the reliability of the findings.

Despite these contributions, this research is not without limitations. First, the study focused solely on the textile sector within a single national context (Turkey), which may limit the generalizability of the results to other industries or countries with differing regulatory, technological, and market conditions. Second, although six expert decision-makers from diverse professional backgrounds were involved, the model's outputs could vary with a larger or more diversified expert group. Third, while the picture-fuzzy approach offers enhanced realism in modeling hesitancy and neutrality, it may introduce complexity in application for practitioners unfamiliar with fuzzy logic methodologies.

Future research can build on this work in several directions. First, cross-sectoral applications of the PF-Entropy–MARCOS model can be explored to test its adaptability in other industries such as healthcare, logistics, or renewable energy. Second, researchers may consider integrating additional decision-making tools (e.g., ANP, DEMATEL, or TODIM) to analyze interdependencies among criteria or capture decision-makers' risk preferences. Third, incorporating dynamic data streams (e.g., real-time service performance metrics and user reviews) could enhance the responsiveness and relevance of the decision model in rapidly changing business environments. Lastly, developing user-friendly software or decision-support interfaces based on this model could significantly facilitate adoption by SMEs lacking technical expertise in MCDM methodologies.

This study contributes theoretically and practically to decision science and SME management by offering a novel and validated framework to support high-stakes strategic decisions under uncertainty. With further refinement and broader applications, the proposed model holds strong potential to become a widely used tool in contemporary business environments.

Appendix

Table A
Linguistic evaluations of decision-makers on alternatives

Alternatives	DM	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A1	DM1	ÇÇY	ÇY	ÇÇY	ÇY	ÇÇY	ÇÇY	ÇÇD	ÇÇY	OY	ÇÇY	OY	ÇÇY
	DM2	ÇY	ÇY	ÇÇY	ÇY	ÇÇY	ÇÇY	ÇÇD	ÇÇY	OY	ÇY	OY	ÇÇY
	DM3	ÇY	Y	Y	ÇY	ÇÇY	ÇY	ÇÇD	ÇY	O	ÇY	O	ÇY
	DM4	OY	O	OY	O	OY	OY	ÇÇD	OY	D	OY	D	OY
	DM5	Y	O	OY	O	Y	OY	ÇÇD	OY	D	OY	D	OY
	DM6	ÇY	ÇY	ÇÇY	ÇY	ÇÇY	ÇÇY	ÇÇD	ÇÇY	O	ÇÇY	OY	ÇÇY
A2	DM1	Y	ÇÇY	ÇY	ÇÇY	OD	ÇÇY	ÇÇD	ÇY	OD	ÇY	Y	O
	DM2	Y	ÇÇY	ÇY	ÇÇY	OD	ÇY	ÇD	ÇY	OD	ÇY	Y	O
	DM3	OY	ÇY	Y	D	OD	ÇY	ÇÇD	Y	D	Y	OY	OD
	DM4	OD	OY	O	OY	ÇÇD	OY	ÇÇD	O	ÇÇD	O	OD	ÇD
	DM5	OD	OY	O	OY	ÇÇD	OY	ÇÇD	O	ÇÇD	O	OD	ÇD
	DM6	Y	ÇÇY	ÇY	ÇÇY	OD	ÇY	ÇÇD	ÇY	OD	ÇY	Y	O
A3	DM1	ÇD	ÇÇY	ÇY	O	D	OY	ÇÇY	OY	ÇD	ÇD	O	ÇÇD
	DM2	ÇD	ÇÇY	ÇY	O	D	OY	ÇÇY	OY	ÇD	ÇD	O	ÇÇD
	DM3	ÇÇD	ÇY	Y	OD	ÇD	O	ÇY	O	ÇÇD	ÇÇD	OD	ÇÇD
	DM4	ÇÇD	OY	O	ÇD	ÇÇD	D	OY	D	ÇÇD	ÇÇD	ÇD	ÇÇD
	DM5	ÇÇD	OY	O	ÇD	ÇÇD	D	Y	D	ÇÇD	ÇÇD	ÇD	ÇÇD
	DM6	ÇD	ÇÇY	ÇY	O	D	OY	ÇÇY	OY	ÇD	D	O	ÇÇD

Table A
Continued

Alternatives	DM	C1	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12
A4	DM1	D	ÇÇY	OY	D	O	Y	ÇÇD	Y	O	OD	O	ÇD
	DM2	D	ÇÇY	OY	D	O	Y	ÇÇD	Y	O	OD	O	ÇD
	DM3	ÇD	ÇY	O	ÇD	OD	OY	ÇÇD	OY	OD	D	OD	ÇÇD
	DM4	ÇÇD	OY	D	ÇÇD	ÇD	OD	ÇÇD	OD	ÇD	ÇÇD	ÇD	ÇÇD
	DM5	ÇÇD	OY	D	ÇÇD	ÇD	OD	ÇÇD	OD	ÇD	ÇÇD	ÇD	ÇÇD
	DM6	D	ÇÇY	OY	D	O	Y	ÇÇD	Y	O	OD	O	ÇD
A5	DM1	ÇD	ÇÇY	ÇY	ÇD	OY	OD	ÇÇD	OD	OD	D	ÇD	ÇÇD
	DM2	ÇD	ÇÇY	ÇY	ÇD	O	OD	ÇÇD	OD	OD	D	ÇD	ÇÇD
	DM3	ÇÇD	ÇY	Y	ÇÇD	O	D	ÇÇD	D	D	ÇD	ÇÇD	ÇÇD
	DM4	ÇÇD	OY	O	ÇÇD	D	ÇÇD	ÇÇD	ÇÇD	ÇÇD	ÇÇD	ÇÇD	ÇÇD
	DM5	ÇÇD	OY	O	ÇÇD	D	ÇÇD	ÇÇD	ÇÇD	ÇÇD	ÇÇD	ÇÇD	ÇÇD
	DM6	ÇD	ÇÇY	ÇY	ÇD	OY	OD	ÇÇD	OD	OD	D	ÇD	D
A6	DM1	ÇÇD	ÇY	O	ÇD	OY	Y	ÇÇD	O	ÇÇD	ÇÇD	O	ÇÇD
	DM2	ÇÇD	ÇY	O	ÇD	OY	Y	ÇÇD	O	ÇÇD	ÇÇD	O	ÇÇD
	DM3	ÇÇD	Y	OD	ÇÇD	O	OY	ÇÇD	OD	ÇÇD	ÇÇD	OD	ÇÇD
	DM4	ÇÇD	O	ÇD	ÇÇD	D	OD	ÇÇD	ÇD	ÇÇD	ÇÇD	ÇD	ÇÇD
	DM5	ÇÇD	O	ÇD	ÇÇD	D	OD	ÇÇD	ÇD	ÇD	ÇÇD	ÇD	ÇÇD
	DM6	ÇÇD	ÇY	O	ÇD	OY	Y	ÇÇD	O	ÇÇD	ÇÇD	O	ÇÇD
A7	DM1	Y	ÇÇY	OY	ÇY	D	OD	ÇÇD	O	ÇÇY	OY	O	OY
	DM2	Y	ÇÇY	OY	ÇY	D	OD	ÇÇD	O	ÇÇY	OY	O	OY
	DM3	OY	ÇY	O	Y	ÇD	D	ÇÇD	OD	ÇY	O	OD	O
	DM4	OD	OY	D	O	ÇÇD	ÇÇD	ÇÇD	ÇD	OY	D	ÇD	D
	DM5	OD	OY	D	O	ÇÇD	ÇÇD	ÇÇD	ÇD	OY	D	ÇD	D
	DM6	Y	ÇY	OY	ÇY	D	OD	ÇÇD	O	ÇÇY	OY	O	OY
A8	DM1	D	ÇÇY	Y	OD	ÇÇY	OY	OD	Y	O	ÇD	ÇD	ÇD
	DM2	D	ÇÇY	Y	OD	ÇÇY	OY	OD	Y	O	ÇD	ÇD	ÇD
	DM3	ÇD	ÇY	OY	D	ÇY	O	D	OY	OD	ÇÇD	ÇÇD	ÇÇD
	DM4	ÇÇD	OY	OD	ÇÇD	OY	D	ÇÇD	OD	ÇD	ÇÇD	ÇÇD	ÇÇD
	DM5	ÇÇD	O	OD	ÇÇD	OY	D	ÇÇD	OD	ÇD	ÇÇD	ÇÇD	ÇÇD
	DM6	D	ÇÇY	Y	OD	ÇÇY	OY	OD	Y	O	ÇD	ÇD	ÇD
A9	DM1	OY	ÇY	Y	ÇY	Y	ÇÇY	ÇÇD	ÇY	O	OY	ÇÇY	O
	DM2	OY	ÇY	Y	ÇY	Y	ÇY	ÇÇD	ÇY	O	OY	ÇY	O
	DM3	O	Y	OY	Y	OY	ÇY	ÇÇD	Y	OD	O	ÇY	OD
	DM4	D	O	OD	O	OD	ÇÇY	ÇÇD	O	ÇD	D	OY	ÇD
	DM5	D	O	OD	O	OD	ÇY	ÇÇD	O	ÇD	D	OY	ÇD
	DM6	OY	ÇY	Y	ÇY	Y	ÇY	ÇÇD	ÇY	O	OY	ÇÇY	O

Author Contributions

Conceptualization, C.N.D. and Ö.F.G.; methodology, Ö.F.G.; validation, Ö.F.G.; formal analysis, Ö.F.G.; investigation, Ö.F.G.; resources, Ö.F.G.; data curation, Ö.F.G.; writing—original draft preparation, Ö.F.G. and Ö.F.G.; writing—review and editing, Ö.F.G. and Ö.F.G.; visualization, Ö.F.G.; supervision, Ö.F.G.; project administration, Ö.F.G.. All authors have read and agreed to the published version of the manuscript.

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Conflicts of Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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