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Efficient Outranking Framework Based on CoCoSo Method and T-Spherical Fuzzy Environments

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ABSTRACT

College-level sports involve competitive athletic programs organized by universities and colleges, encompassing various disciplines. These programs require strategic decision-making at multiple levels, including athlete recruitment and financial management. Coaches, athletic directors, and sports analysts use data-driven approaches, performance metrics, and multi-criteria decision-making (MCDM) techniques to optimize team performance and resource allocation. To achieve the goal of this manuscript, we apply a broader framework for T-spherical fuzzy sets (T-SFS) to manage uncertainty in expert opinions during the aggregation process. To mitigate the impact of redundant and incomplete information on decision-makers, we developed a decision algorithm based on the CoCOSo method for resolving real-world applications and numerical examples using mathematical aggregation operators. To assess the superiority of the discussed decision-making technique and fuzzy framework, we conducted an experimental case study to evaluate a chosen expert for a football ground using different criteria and key components. A sensitivity analysis is also conducted to demonstrate the consistency and reliability of the diagnosed mathematical terminology.

1. Introduction

In college football, the dominant model on which training is based remains one of discovering universal educational paradigms rather than considering the contextual educational worth of exploratory matters. This stands in clear contrast to the findings of educational research. Often, in environments that increase their dependence on others' efficacy, schools and colleges fail to engage with the concept of self-organization in their football tuition process [1]. Self-organization and other organizations are the only guides to a company's long-term performance. This assertion creates a contradiction: students exercise their own subjective and creative initiative and self-organization, rendering teaching resources [2] useless. Today, football education programs at most universities and institutions rarely use resources beyond the classroom. Such advancements in science and technology, and their impact on society, must be mirrored [3], including teachers' access to educational resources. Teaching resources are maximized only when they are used to capacity.

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Despite these contrasts, college and university football instruction has been drastically curtailed, and indeed this is a significant factor in institutions' inability to generate gifted people with a superb all-round education and exceedingly high talent in the game.

Just like other levels of education, college football is taught and learned as a self-organizing system. The primary objective of self-organization theory is to analyze the emergence and evolution of complex systems that can self-organize [4]. The outdated conceptions and methods of football teaching are challenged by sharpened social expectations for sports education today. Some personal differences among the learners are sometimes overlooked in football teaching. The quality of instruction is an issue for some football educators [5]. Because of this educational concept, teachers' skills of managing learning in the classroom are confronted with several intelligences. It will lead to better-quality teaching staff because teachers will be motivated to enhance their skills and expertise. This standard of educational evaluation includes lesson plans, learning goals, instructional resources, instructional methods, and instructional evaluation for football instruction of college athletes [6]. As the paradigms of teaching change, the time for democratization, individualization, and variety has come. The goal of teaching in multiple intelligences should be broadened to include training in essential knowledge and skills to promote the well-rounded development of students, in addition to health promotion, practicality, sustainability, and the fulfillment of individual needs.

The optimization process for the approach, including its flowchart and calculation steps, is shown, with the PSO algorithm as an example. The new and improved PSO algorithm's underlying principles are biological phenomena and rules, just as in the dynamic multispecies particle swarm approach using the food chain mechanism. It also means a food chain, reproductive process , and measures to promote the algorithm [7]. It indicates that the improved PSO method's optimization effect and optimization ability are better than those of the ordinary PSO method, and that it becomes more difficult to find local optima. Moreover, it drastically affected the approach for multi-peak scenarios [8]. As a result, many football teachers do not seriously reflect on how factors beyond their physical or intellectual state influence their students' potential to lead a life in which they maintain physical activity throughout. Given the popularity of college football nationwide, physical education teachers should experiment with new evaluation techniques and metrics [9]. In China, the teaching and development of sports in young students is regarded as the focus of school physical education to form a "lifelong sports society." However, China's "school sports program" also has many problems [10]. Most traditional football players' training plans focus on strength or speed training. Continuous training in a single area for an extended period may harm a player's physical function, and improving performance may not be the best goal [11]. Computer platforms are widely used across various universities for operational applications. Therefore, many scientific and technology colleges have installed multimedia computer rooms for student instruction. This educational mode requires installing the hardware and software [12].

To manage vagueness and uncertainty in insufficient information of expert's opinions, Zadeh [13] initiated a novel theory of fuzzy set (FS) by expressing the belongingness of an object with membership grade (MG) from the closed interval $[0,1]$. The FS has been used to resolve many real-world applications and numerical examples. Later, Atanassov [14] proposed a new approach to intuitionistic fuzzy sets (IFSs) by introducing the non-membership grade (NMG) into the theory of FSs. Yager [15] enhanced the structure of IFSs by introducing a novel approach to Pythagorean FSs (PyFSs). Furthermore, Yager [16] modified the concept of q-rung orthopair FS (q-ROFS). The theory of FSs and their generalization has been applied to fix uncertainties and vagueness during the decision analysis process. Cuong [17] proposed a new framework for picture fuzzy sets (PFS) with four components: MG, NMG, abstinence grade (AG), and refusal grade. Mahmood *et al*. [18] gave concepts of spherical FSs (SFSs) and t-spherical FSs (T-SFSs). The generalization of fuzzy frameworks discussed above has been applied to many real-world applications.

Rukhsar *et al*. [19] analyzed the performance of power aggregation operators using the circular intuitionistic fuzzy framework. Hussain *et al*. [20] utilized different mathematical approaches to classify renewable energy sources. Hussain *et al*. [21] developed Sugeno-Weber aggregation operators for decision-making problems. Hussain *et al*. [22] enhanced the reliability of the fuzzy framework by investigating established criterion weights and advanced decision-making processes. Hussain *et al*. [23] utilized properties of Heronian mean aggregation operators in the context of decision-making models. Hussain *et al*. [24] applied various aggregation operators and decision-making methods to assess construction materials. Wang *et al*. [25] discussed the qualities of different solar panels using Sugeno-Weber mathematical approaches and decision-making processes. Mahmood and Ali [26] introduced a novel theory of a complex intuitionistic fuzzy framework to manage uncertainty in professional experts' judgments. Mahmood and Ali [27] modified Aczel-Alsina aggregation models using complex intuitionistic fuzzy situations. Ali *et al*. [28] proposed a novel TOPSIS theory for complex spherical fuzzy domains. Riaz and Farid [29] demonstrated the reliability of green supply chain enterprises using the linear Diophantine fuzzy framework. Riaz and Farid [30] modified the algebraic operations to develop new mathematical approaches to Linear Diophantine fuzzy terminologies and decision-making models. Ayub *et al*. [31] introduced a robust decision analysis technique by elaborating on the theory of rough sets. Akram and Martino [32] delved into a dominant decision-making model based on a fuzzy rough set system with aggregation operators. Akram *et al*. [33] diagnosed a particular outranking approach for digital transportation systems. Akram *et al*. [34] developed hybrid decision-making models to handle uncertainty and vagueness during the aggregation process. Diao and Wei [35] discussed a novel approach to resolving decision-making problems using information from a group of experts. Senapati *et al*. [36] discussed the qualities of decision-making models and investigated a reliable transportation system. Chakraborty *et al*. [37] proposed the Combined Compromise Solution (CoCoSo) method to address insufficient information during the aggregation process. Nguyen *et al*. [38] proposed a hybrid decision-making model using advanced artificial intelligence techniques. Yazdani *et al*. [39] also applied the CoCoSo method for handling expert's opinions under different criteria. Garg *et al*. [40] utilized properties of similarity measures with Hamy mean operators. Jaleel [41] discussed the characteristics of the agricultural robotic System using the Dombi aggregation operator and decision-making problem. Shahzadi *et al*. [42] established a robust ranking method using the VIKOR method under consideration of Pythagorean fuzzy frameworks.

The T-SFSs have gained significant attention in decision-making models due to their ability to handle uncertainty and imprecise information, their application in sports-related evaluations remains largely unexplored. In particular, the assessment of football grounds for college-level sports events involves multiple criteria, such as field conditions, safety measures, and infrastructure quality, which are often subject to subjective judgments and varying expert opinions. Existing evaluation methods primarily rely on traditional fuzzy or intuitionistic approaches, which may not fully capture the complexity and hesitancy inherent in such assessments. Despite the growing need for robust decision-making frameworks in sports facility management, there is a lack of research integrating T-

SFS into this domain. The potential of T-SFS to enhance decision accuracy and reflect real-world uncertainties in football ground evaluation has not been adequately investigated. This gap highlights the need to develop novel T-SFS-based decision-making models to evaluate college football grounds, ensuring fair, consistent, and data-driven assessments for sports event planning. The main theme of the article is discussed as follows:

1) To apply a broader framework of fuzzy systems to handle uncertainty and vagueness during decision analysis and the aggregation process.
2) Formulate comparison rules in the light of t-spherical fuzzy context and algebraic expressions.
3) We also established a step-wise decision-making algorithm for the CoCoSo method using the mathematical terminology of t-spherical fuzzy situations that we developed.
4) A coaching expert evaluated the step-wise decision algorithm of the CoCoSo method and the mathematical approaches of the fuzzy framework.
5) A sensitivity analysis is also conducted to demonstrate the effectiveness and superiority of the proposed mathematical approaches.

The remaining sections of this manuscript are maintained as follows: Section 2 elaborates on basic concepts of fuzzy frameworks and decision-making models. Section 3 presents a problem statement for evaluating games, especially football. Furthermore, advanced methodologies and decision-making techniques are also presented in Section 4. To assess the validity of the mathematical approaches, we present a case study using numerical examples and aggregation operators in Section 5. At the end, Section 6 provides a summary of the manuscript.

2. Preliminaries

Here, we present a brief overview of the fuzzy framework with flexible operations and comparison rules. We also present the basic preliminaries of PFSs and TSFSs, including fundamental operations.

Definition 1: [17] A PFS A is characterized as follow:

$$A = \{\text{ƀ}, (\mathcal{I}(\text{ƀ}), \varphi(\text{ƀ}), \psi(\text{ƀ}))|\text{ƀ} \in \hat{\mathrm{W}}\}$$

As $\mathcal{I}(\text{ƀ}): \hat{\mathrm{W}} \to [0,1], \varphi(\text{ƀ}): \hat{\mathrm{W}} \to [0,1]$ and $\psi(\text{ƀ}): \hat{\mathrm{W}} \to [0,1]$ indicate the satisfaction degree (SD), neutral degree (ND), and dissatisfaction degree (DSD), respectively, and a PFS holds such condition:

$$0 \leq \mathcal{I}(\text{ƀ}) + \varphi(\text{ƀ}) + \psi(\text{ƀ}) \leq 1$$

The refusal index of a PFS is given by $r(\text{ƀ}) = 1 - (\mathcal{I}(\text{ƀ}) + \varphi(\text{ƀ}) + \psi(\text{ƀ}))$. A picture fuzzy value (PFV) is denoted by $\text{ß} = (\mathcal{I}, \varphi, \psi)$.

Definition 2: [18] Let $\hat{\mathrm{W}}$ be a non-empty set and a T-SFS A is characterized as follow:

$$A = \{\text{ƀ}, (\mathcal{I}(\text{ƀ}), \varphi(\text{ƀ}), \psi(\text{ƀ}))|\text{ƀ} \in \hat{\mathrm{W}}\}$$

As $\mathcal{I}: \hat{\mathrm{W}} \to [0,1]$, $\varphi: \hat{\mathrm{W}} \to [0,1]$ and $\psi: \hat{\mathrm{W}} \to [0,1]$ indicate the truth index (TI), neutral index (NI), and falsity index (FI), respectively, and a T-SFS holds such a condition:

$$0 \leq \mathcal{I}^{\text{ŧ}}(\text{ƀ}) + \varphi^{\text{ŧ}}(\text{ƀ}) + \psi^{\text{ŧ}}(\text{ƀ}) \leq 1, \text{ŧ} \in \mathbb{Z}^{+}$$

The refusal index of a T-SFS is given by $r(ƀ) = \sqrt[ŧ]{1 - \left(\mathcal{J}^{ŧ}(ƀ) + \varphi^{ŧ}(ƀ) + \psi^{ŧ}(ƀ)\right)}$. A T-spherical fuzzy value (T-SFV) is denoted by $\text{Ɣ} = \left(\mathcal{J}(ƀ), \varphi(ƀ), \psi(ƀ)\right)$.

Definition 3: [43] For three T-SFVs $\text{Ɣ} = \left(\mathcal{J}(ƀ), \varphi(ƀ), \psi(ƀ)\right), \text{Ɣ}_1 = \left(\mathcal{J}_1(ƀ), \varphi_1(ƀ), \psi_1(ƀ)\right)$ and $\text{Ɣ}_2 = \left(\mathcal{J}_2(ƀ), \varphi_2(ƀ), \psi_2(ƀ)\right)$. Then some necessary operations are expressed as follows:

1) $\text{Ɣ}_1 \subseteq \text{Ɣ}_2$, *if* $\mathcal{J}_1(ƀ) \leq \mathcal{J}_2(ƀ), \varphi_1(ƀ) \geq \varphi_2(ƀ)$ *and* $\psi_1(ƀ) \geq \psi_2(ƀ)$
2) $\text{Ɣ}_1 = \text{Ɣ}_2$, *if* $\text{Ɣ}_1 \subseteq \text{Ɣ}_2$ *and* $\text{Ɣ}_1 \supseteq \text{Ɣ}_2$
3) $\text{Ɣ}_1 \cup \text{Ɣ}_2 = \left\{\begin{matrix} max\left(\mathcal{J}_1(ƀ), \mathcal{J}_2(ƀ)\right), \\ min\left(\varphi_1(ƀ), \varphi_2(ƀ)\right), \\ min\left(\psi_1(ƀ), \psi_2(ƀ)\right) \mid (ƀ) \in \hat{\text{W}} \end{matrix}\right\}$
4) $\text{Ɣ}_1 \cap \text{Ɣ}_2 = \left\{\begin{matrix} min\left(\mathcal{J}_1(ƀ), \mathcal{J}_2(ƀ)\right), \\ max\left(\varphi_1(ƀ), \varphi_2(ƀ)\right), \\ max\left(\psi_1(ƀ), \psi_2(ƀ)\right) \mid (ƀ) \in \hat{\text{W}} \end{matrix}\right\}$
5) $\text{Ɣ}^C = \left(\psi(ƀ), \varphi(ƀ), \mathcal{J}(ƀ)\right), \forall\, (ƀ) \in \hat{\text{W}}$

Definition 4: [43] For three T-SFVs $\text{Ɣ} = \left(\mathcal{J}(ƀ), \varphi(ƀ), \psi(ƀ)\right), \text{Ɣ}_1 = \left(\mathcal{J}_1(ƀ), \varphi_1(ƀ), \psi_1(ƀ)\right)$ and $\text{Ɣ}_2 = \left(\mathcal{J}_2(ƀ), \varphi_2(ƀ), \psi_2(ƀ)\right)$ with $¢ > 0$. Then, we have:

1) $\text{Ɣ}_1 \oplus \text{Ɣ}_2 = \left(\begin{matrix} \sqrt[ŧ]{\mathcal{J}_1^{ŧ}(ƀ) + \mathcal{J}_2^{ŧ}(ƀ) - \mathcal{J}_1^{ŧ}(ƀ).\mathcal{J}_2^{ŧ}(ƀ)}, \\ \varphi_1(ƀ).\varphi_2(ƀ), \psi_1(ƀ).\psi_2(ƀ) \end{matrix}\right)$
2) $\text{Ɣ}_1 \otimes \text{Ɣ}_2 = \left(\begin{matrix} \mathcal{J}_1(ƀ).\mathcal{J}_2(ƀ), \\ \sqrt[ŧ]{\varphi_1^{ŧ}(ƀ) + \varphi_2^{ŧ}(ƀ) - \varphi_1^{ŧ}(ƀ).\varphi_2^{ŧ}(ƀ)}, \\ \sqrt[ŧ]{\psi_1^{ŧ}(ƀ) + \psi_2^{ŧ}(ƀ) - \psi_1^{ŧ}(ƀ).\psi_2^{ŧ}(ƀ)} \end{matrix}\right)$
3) $¢\text{Ɣ} = \left(\sqrt[ŧ]{1 - \left(1 - \mathcal{J}^{ŧ}(ƀ)\right)^{¢}}, \varphi^{¢}(ƀ), \psi^{¢}(ƀ)\right)$
4) $\text{Ɣ}^{¢} = \left(\mathcal{J}^{¢}(ƀ), \sqrt[ŧ]{1 - \left(1 - \varphi^{ŧ}(ƀ)\right)^{¢}}, \sqrt[ŧ]{1 - \left(1 - \psi^{ŧ}(ƀ)\right)^{¢}}\right)$

Definition 5: [44] For any T-SFV $\text{Ɣ} = \left(\mathcal{J}(ƀ), \varphi(ƀ), \psi(ƀ)\right)$, we can express the score function and accuracy function as follows:

$$\mathcal{S}(\text{Ɣ}) = \frac{1}{2}\left(1 + \mathcal{J}^{ŧ}(ƀ) - \varphi^{ŧ}(ƀ) - \psi^{ŧ}(ƀ)\right), \mathcal{S}(\text{Ɣ}) \in [0,1]$$

and

$$\mathcal{A}(\text{Ɣ}) = \frac{1}{2}\left(\mathcal{J}^{ŧ}(ƀ) + \varphi^{ŧ}(ƀ) + \psi^{ŧ}(ƀ)\right), \mathcal{A}(\text{Ɣ}) \in [0,1]$$

3. Problem Statement

Evaluating football grounds for college-level sports events involves a comprehensive assessment of various factors to ensure they meet the required standards for hosting competitive matches. One primary consideration is the field's dimensions and surface quality. The playing area must adhere to official size regulations, providing a level, well-maintained surface that facilitates fair play and minimizes injury risk. Regular maintenance, including mowing, aeration, and pest control, is essential to maintaining the turf's integrity throughout the season.

Another critical aspect is the availability and condition of supporting facilities. Adequate seating arrangements are necessary to accommodate spectators comfortably, ensuring clear sightlines and accessibility. Proper lighting systems are essential for evening matches, providing sufficient illumination to ensure player safety and optimal viewing. Additionally, well-equipped locker rooms should be available to provide athletes with secure and hygienic spaces for changing and preparation. The presence of medical facilities or first-aid stations is also crucial for promptly addressing injuries during events. Accessibility and compliance with safety regulations are paramount in the evaluation process. The venue should be easily reachable for teams and spectators, with ample parking facilities and clear signage. Ensuring compliance with local building codes and safety standards is essential to prevent accidents and legal issues. This includes installing appropriate fencing, emergency exits, and crowd-control measures to manage large gatherings effectively. By meticulously assessing these elements, institutions can provide a safe and enjoyable environment for all participants and attendees during college-level football events.

4. Decision-Making Methodology

To improve the traditional decision-making approach to the MADM problem, the combined theory of the CoCoSo method and t-spherical fuzzy information is superior to the simple decision-making process. This is especially important in the selection of a professional expert to improve the quality and fitness of football players. To serve this purpose, consider a set of finite alternatives and attributes denoted by $A = \{\ddot{\mathrm{V}}_1, \ddot{\mathrm{V}}_2, \ddot{\mathrm{V}}_3, \cdots, \ddot{\mathrm{V}}_m\}$ and $C = \{c_1, c_2, c_3, \cdots, c_n\}$, respectively. Suppose that a set of weight criteria is denoted by $\{\omega_1, \omega_2, \omega_3, \cdots, \omega_n\}$ such that $\sum_{i=1}^{n} \omega_i = 1$. The assessment of the professional expert uses the following step-wise decision algorithm of the CoCoSo method as follows:

Step 1: The decision matrix arranges information of various attributes corresponding to each alternative as follows:

$$\mathcal{DM} = \begin{pmatrix} \mathfrak{S}_{11} & \mathfrak{S}_{12} & \cdots & \mathfrak{S}_{1n} \\ \mathfrak{S}_{21} & \mathfrak{S}_{22} & \cdots & \mathfrak{S}_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \mathfrak{S}_{m1} & \mathfrak{S}_{m2} & \cdots & \mathfrak{S}_{mn} \end{pmatrix}$$

Where, $\mathfrak{S}_{ij} = \left(\mathcal{J}_{ij}(\mathrm{ƀ}), \varphi_{ij}(\mathrm{ƀ}), \psi_{ij}(\mathrm{ƀ})\right)$ indicate a T-SFV associated with each attribute corresponding to each alternative.

Step 2: To demonstrate the type of attributes if there are more than one type of criteria. We must change the nature of different attributes in a decision matrix $DM = [a_{ij}]_{m\times n}$into a normalized decision matrix $\mathcal{DM}^N = \left(\mathfrak{S}_{ij}^n\right)_{m\times n}$. For this purpose, we normalized the types of criteria using the following expression:

$$\mathcal{D}^N = \begin{pmatrix} \mathfrak{S}_{11}^n & \mathfrak{S}_{12}^n & \cdots & \mathfrak{S}_{1n}^n \\ \mathfrak{S}_{21}^n & \mathfrak{S}_{22}^n & \cdots & \mathfrak{S}_{2n}^n \\ \vdots & \vdots & \ddots & \vdots \\ \mathfrak{S}_{m1}^n & \mathfrak{S}_{m2}^n & \cdots & \mathfrak{S}_{mn}^n \end{pmatrix}$$

where,

$$\mathfrak{S}_{ij}^n = \begin{cases} \left(\mathcal{J}_{ij}(\text{ƀ}), \varphi_{ij}(\text{ƀ}), \psi_{ij}(\text{ƀ})\right) & for\ Beneficial\ attributes \\ \left(\psi_{ij}(\text{ƀ}), \varphi_{ij}(\text{ƀ}), \mathcal{J}_{ij}(\text{ƀ})\ \right) & for\ non-Beneficial\ attributes \end{cases}$$

Step 3: To defuzzify each triplet in the criteria, we apply the following formula of the score function as follows:

$$scr\mathfrak{S}_{ij}^n = \frac{1}{2}\left(1 + \mathcal{J}_{ij}^{\text{ŧ}}(\text{ƀ}) - \varphi_{ij}^{\text{ŧ}}(\text{ƀ}) - \psi_{ij}^{\text{ŧ}}(\text{ƀ})\right)$$

Step 4: Here, estimate the weighted normalized decision matrix using external weights of criteria or attributes. The weighted normalized decision matrix $\left[B_{ij}\right]_{m\times n}$ is illustrated based on the following expression.

$$B_{ij} = w_j.scr\mathfrak{S}_{ij}^n$$

Step 5: In this step, we have to compute the sum of each weighted normalized value of the attributes corresponding to alternatives using the following expression.

$$\mathcal{S}_i = \sum_{j=1}^{n} B_{ij}$$

Step 6: The results of the product of the weighted normalized values is obtained based on the following expression.

$$P_i = \prod_{j=1}^{n} B_{ij}$$

Step 7: The following expression is applied to calculate the average of the sum and product of the weighted normalized values based on the previous two steps 6 and 7:

$$A_i = \frac{P_i + \mathcal{S}_i}{2}$$

Step 8: Based on the previous aggregated results, we determine the relative importance associated with each alternative as follows:

$$C_i = A_i.\left(1 + \frac{\mathcal{S}_i - min\mathcal{S}_i}{max\mathcal{S}_i - min\mathcal{S}_i} + \frac{P_i - minP_i}{max\mathcal{S}_i - min\mathcal{S}_i}\right)$$

Step 9: Investigate the ranking of preferences or alternatives based on the computed relative importance scores. The highest value of relative importance indicates a more suitable optimal option.

5. Illustrative Numerical Example

In this case study, we evaluated the profiles of different coaching experts under different circumstances using t-spherical fuzzy information and advanced decision-making techniques from the CoCoSo method. For this purpose, consider that we have five different applications for coaching experts as $\{\ddot{V}_1, \ddot{V}_2, \ddot{V}_3, \ddot{V}_4, \ddot{V}_5\}$. These professional experts are evaluated under the circumstances of five criteria: (Ethical and Professional Conduct Ꝕ$_1$; Educational Background and Certifications Ꝕ$_2$ Leadership and Communication Skills Ꝕ$_3$; Coaching Experience Ꝕ$_4$; Past Achievements and Records Ꝕ$_5$)

The evaluation and integration of coaching experts are done using different weights for the above-discussed selection attributes. The assessment process for coaching experts using the step-wise decision algorithm of the CoCoSo method for the MADM problem is as follows. Information about each alternative is presented in Table 1.

Table 1
Demonstrates Information About Coaching Experts Under the System of T-Spherical Fuzzy Framework

	Ꝕ$_1$	Ꝕ$_2$	Ꝕ$_3$	Ꝕ$_4$	Ꝕ$_5$
$\ddot{V}_1$	$(0.34, 0.17; 0.11)$	$(0.19, 0.16; 0.22)$	$(0.28, 0.11; 0.17)$	$(0.17, 0.14; 0.26)$	$(0.19, 0.21; 0.27)$
$\ddot{V}_2$	$(0.23, 0.37; 0.26)$	$(0.28, 0.23; 0.37)$	$(0.34, 0.28; 0.22)$	$(0.23, 0.33; 0.34)$	$(0.25, 0.26; 0.35)$
$\ddot{V}_3$	$(0.65, 0.45; 0.43)$	$(0.36, 0.27; 0.45)$	$(0.39, 0.43; 0.33)$	$(0.21, 0.49; 0.37)$	$(0.38, 0.32; 0.31)$
$\ddot{V}_4$	$(0.32, 0.28; 0.48)$	$(0.29, 0.31; 0.55)$	$(0.47, 0.38; 0.23)$	$(0.38, 0.21; 0.43)$	$(0.43, 0.39; 0.35)$
$\ddot{V}_5$	$(0.28, 0.48; 0.34)$	$(0.19, 0.16; 0.27)$	$(0.43, 0.46; 0.27)$	$(0.21, 0.32; 0.28)$	$(0.48, 0.46; 0.45)$

Further, we compute the score values for all alternatives using Score functions to defuzzify the T-SFVs and obtain the cumulative human opinion for each alternative on each attribute. The score values for each T-SFV are given in Table 2. In this case study, the decision considers a beneficial criterion. So, the normalization process here is unnecessary.

Table 3
Computed score functions of each attribute corresponding to each alternative

	Ꝕ$_1$	Ꝕ$_2$	Ꝕ$_3$	Ꝕ$_4$	Ꝕ$_5$
$\ddot{V}_1$	0.5165	0.4961	0.5079	0.4923	0.4890
$\ddot{V}_2$	0.4720	0.4796	0.5034	0.4685	0.4776
$\ddot{V}_3$	0.5520	0.4679	0.4719	0.4205	0.4962
$\ddot{V}_4$	0.4501	0.4141	0.5184	0.4831	0.4887
$\ddot{V}_5$	0.4360	0.4915	0.4812	0.4773	0.4611

Table 3 shows the score values for the alternatives. Now, we evaluate the WNDM with the help of Table 2. The WNMD obtained is given in Table 3 below.

Table 3
Results of weighted normalized decision matrix.

	Ꝕ$_1$	Ꝕ$_2$	Ꝕ$_3$	Ꝕ$_4$	Ꝕ$_5$
$\ddot{V}_1$	0.0930	0.1191	0.0813	0.1378	0.0685

$\grave{\grave{V}}_2$	0.0850	0.1151	0.0805	0.1312	0.0669
$\grave{\grave{V}}_3$	0.0994	0.1123	0.0755	0.1177	0.06695
$\grave{\grave{V}}_4$	0.0810	0.0994	0.0829	0.1353	0.0684
$\grave{\grave{V}}_5$	0.0785	0.1180	0.0770	0.1336	0.0645

The sum and product of the attributes for each alternative were calculated to obtain the overall solutions for the alternatives. Table 4 presents the calculated sums and products for each alternative. Subsequently, the average values of the sums and products were determined. Finally, the relative scores for each alternative were calculated based on these values and are also presented in Table 4.

Table 4
Demonstrates different results, including summation, product, average, and the relative scores for each alternative.

	Sum	Product	Average	Relative scores
$\grave{\grave{V}}_1$	0.4996	8.49	0.2498	0.7494
$\grave{\grave{V}}_2$	0.4786	6.91	0.2393	0.7179
$\grave{\grave{V}}_3$	0.4774	6.89	0.2372	0.7116
$\grave{\grave{V}}_4$	0.4670	6.18	0.2335	0.7005
$\grave{\grave{V}}_5$	0.4716	6.15	0.2358	0.7075

Finally, we rank the alternatives based on the relative scores obtained in Table 4. As the alternative $\grave{\grave{V}}_1$ Thus, it has the greatest relative score, it is considered the best alternative. Consequently, the ranking of the alternatives obtained is $\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$. The ranking of the alternatives is graphically represented in Figure 1 below.

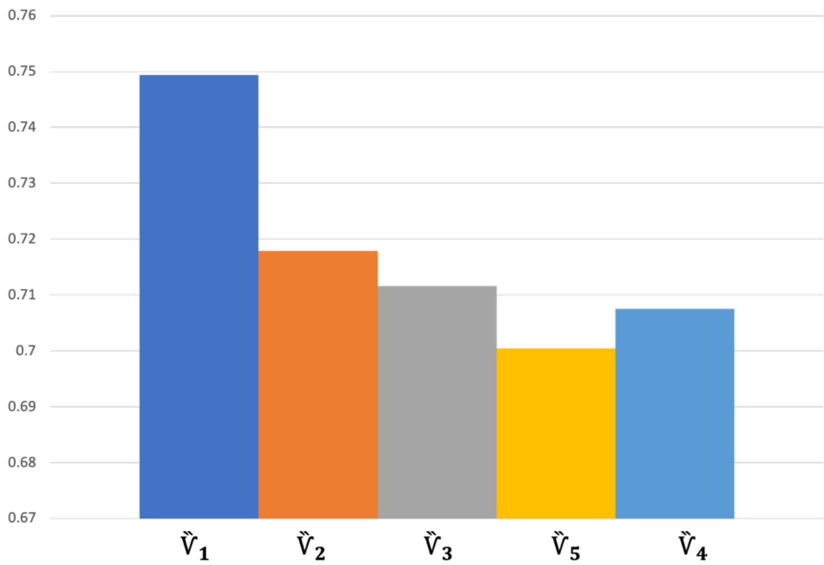

Fig. 1 shows the final ranking based on the computed score functions of each applicant.

5.1 Sensitivity Analysis

Additionally, a parameter ƫ is included in the constructed model. As a result, the established strategy gains flexibility. The ranking of the options according to various values of ƫ is shown in the following. The ranking results are displayed in Table 5 below.

Table 5
Ranking of alternatives by the setting of different parametric variables ƫ.

ƫ	Relative scores					Obtained ranking	Results changed
3	0.7494	0.7179	0.7116	0.7005	0.7075	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	No
4	0.7505	0.7387	0.7404	0.7260	0.7326	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
5	0.6930	0.6890	0.6931	0.6814	0.6859	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
6	0.5499	0.5488	0.5522	0.5452	0.5475	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
7	0.4710	0.4706	0.4731	0.4689	0.4701	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
8	0.4213	0.4212	0.4229	0.4203	0.4209	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
9	0.3871	0.3871	0.3882	0.3866	0.3870	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
10	0.3621	0.3620	0.3628	0.3618	0.3620	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
15	0.2966	0.2966	0.2967	0.2966	0.2966	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
20	0.2704	0.2704	0.2704	0.2704	0.2704	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
35	0.2517	0.2517	0.2517	0.2517	0.2517	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
40	0.2507	0.2507	0.2507	0.2507	0.2507	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes
50	0.2501	0.2501	0.2501	0.2501	0.2501	$\grave{\grave{V}}_1 \succ \grave{\grave{V}}_2 \succ \grave{\grave{V}}_3 \succ \grave{\grave{V}}_5 \succ \grave{\grave{V}}_4$	Yes

We have changed the values of ƫ from 3 to 100 and obtained interesting results. At ƫ $= \mathbf{3}$ the most suitable option is $\grave{\grave{V}}_2$. But at ƫ > 3, we obtain different rankings. The most suitable option for ƫ > 3 is $\grave{\grave{V}}_2$ which is consistent. Thus, the decision maker is advised to choose ƫ greater than 3. However, the relative scores obtained after ƫ > 11 are much smaller. Hence, the values of ƫ > 3 and ƫ < 11 can provide comparatively clearer results. Variation in the results with the change in the values of parameter ƫ is given in Figure 2 below.

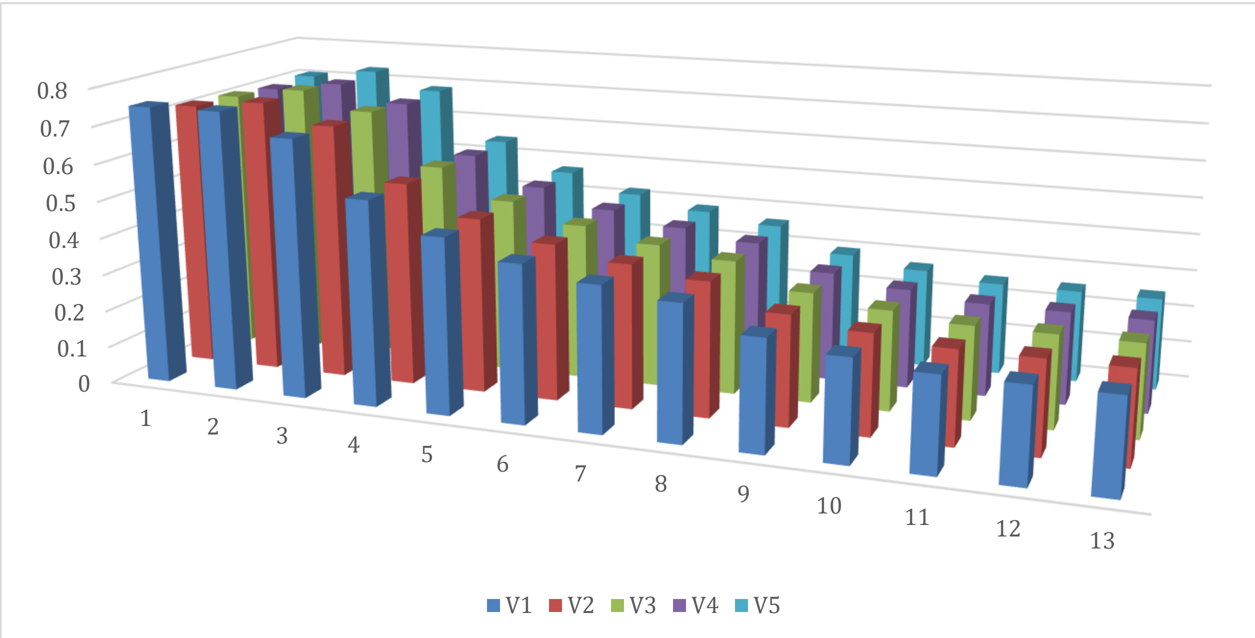

Fig. 2. Ranking of the alternatives at various values of the parameter.

6. Conclusion

The CoCoSo method is an effective multi-attribute decision-making (MADM) approach for selecting professional coaching experts by integrating multiple aggregation strategies to achieve a balanced, reliable ranking. The t-spherical fuzzy System enhances decision-making by handling uncertainty and vagueness in expert opinions, enabling more precise evaluation of coaching candidates. Combining CoCoSo with a t-spherical fuzzy environment improves the accuracy and robustness of the selection process. This approach ensures a comprehensive and fair evaluation by considering multiple criteria, such as coaching experience, technical expertise, leadership skills, and performance analytics. In this article, we evaluated several coaching experts to select football grounds that would improve players' physical fitness under different circumstances. To achieve the main goal of this article, we investigated a ranking of preferences under the System of different criteria and the decision-making technique of the CoCoSo method. To validate the proposed decision-making strategies of the CoCoSo method, a subsection of the sensitivity analysis is conducted using different parametric values for aggregation operators. By using this technique, we observed consistency in the results. We can apply the invented approaches to various complex real-world problems and fuzzy frameworks based on the reliability of the proposed mathematical terminology.

The proposed approach should be further validated on larger and more diverse data sets in various regions and application scenarios. Advanced optimization algorithms, real-time data acquisition, and uncertainty analysis can further enhance the reliability and applicability of the model. Furthermore, a comparison of the proposed framework with other decision-making methods can give more insights into the effectiveness and robustness of the proposed framework. In future studies, alternative MADM methods can be used, such as BWM-TOPSIS [45], AHP-TOPSIS [46], PROMETHEE [47], or MABAC-TOPSIS [48].

Author Contributions

Abrar Hussain fully contributed to this article.

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Data Availability Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Conflicts of Interest

There are no conflicts of interest.

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