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# NEW INTUITIONISTIC FUZZY PARAMETRIC DIVERGENCE MEASURES AND SCORE FUNCTION-BASED COCOSO METHOD FOR DECISION-MAKING PROBLEMS

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***Abstract:*** *The present study introduces a decision-making approach with the combined compromise solution (CoCoSo) under intuitionistic fuzzy sets (IFSs) named as the IF-CoCoSo method based on proposed divergence measures and score function. The aim of the presented approach is to obtain an effective solution for multi-criteria decision-making problems on IFSs context. In this line, a new procedure is presented to derive the criteria weights using generalized score function and parametric divergence measures of IFSs. To compute the criteria weight, a generalized score function and parametric divergence measures are developed on IFSs and discussed some interesting properties. Further, the presented approach is applied to rank and evaluate therapies for medical decision making problems, which demonstrates its applicability and feasibility. Finally, comparative and sensitivity analyses are discussed for validating the developed method.*

**Key words**: *Intuitionistic fuzzy sets, combined compromise solution, medical decision-making, divergence measure, score function.*

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## 1. Introduction

Healthcare decision-making is a multifaceted procedure which involves data processing, assessment of evidence, and application of relevant knowledge in order to choose the suitable interventions. Decision-making in healthcare is challenging for experts because of the high level of ambiguity, complexity of decisions, many tangible and intangible variables, and multiple objectives involved (Basile et al., 2022). For such decisions, "multi-criteria decision-making (MCDM)" approaches are appropriate. MCDM is defined as "an umbrella term to describe a collection of formal methods, which seek to take explicit account of numerous criteria in helping individuals or groups that explore decisions" (Thokala et al., 2016). In the process of healthcare MCDM, Lutz and Bowers (2000) confirmed the capability of patients in making decisions regarding what they want and need. On the other hand, patients' skills and knowledge might be too insufficient to make a significant contribution to final clinical results in the group decision making procedure(Lee and Lin, 2010). If the patient's circumstance and viewpoints are considered well, it will be clear that their judgments are essentially inaccurate, involving lots of uncertainties. Thus, the present paper applies "intuitionistic fuzzy sets (IFSs)" to capture inaccurate or ambiguous therapeutic information that may appear during medical decision-making analyses.

The "fuzzy sets (FSs)" established by Zadeh (1965) is very popular in the decision-making field (Bozanic et al., 2019; Bhattacharya et al., 2022; Torğul et al., 2022). Atanassov (1986) modified the FSs and developed the IFSs that is known as having both "non-membership function (NF)" and "membership function (MF)". The IFS has made available mathematical framework of a higher efficiency in managing the situations in which the "decision-expert (DE)" is of two minds at the same moment whether to approve a certain decision or not. Lot of topics concerning decision making with IFSs have been considered (Stanujkić and Karabašević, 2018; Kumari and Mishra, 2020; Son et al., 2020; Kushwaha et al., 2020; Rahman, 2022; Hezam et al., 2022). "Intuitionistic fuzzy numbers (IFNs)" have been ranked in many situations through their conversion into representative crisp values(Yager, 2004). In case of IFNs, the representative crisp values are noted as score degrees and accuracy degrees. A score function of IFSs was developed by Chen and Tan (1994) using the MF and NF. After that, Hong and Choi (2000) made an improvement on this function through adding an accuracy function to it. Furthermore, in (Wang and Chen, 2018; Zeng et al., 2019), authors have offerred other functions to rank IFNs.

Scholars made use of the divergence measure for the purpose of assessing the discrimination degree between objects. Pal (1993) was a pioneer in the fuzzy divergence measure. Then, the idea of integrating divergence measure with IFSs was introduced by Vlachos and Sergiadis (2007); they used it in segmentation of images, diagnosis of diseases, and recognition of patterns. In recent years, a numerous of divergence measures have been discussed by numerous researchers (Montes et al., 2015; Ansari et al., 2018; Xiao, 2019; Arora & Naithani, 2022). Although, the previous studies have focused on different divergence measures of IFSs, they have not integrated DE preferences with the measure. Additionally, the extant measure is in a linear order; thus, it gives no precise nature of the alternative. As a result, the present study keeps the efficiency and flexibility criteria of IFSs and proposes an innovative generalized parametric directed divergence measure that is capable of measuring the fuzziness of a set. To this end, a divergence measure of order α and β is offered to give higher reliability and flexibility to DEs for various values of these parameters. The formulations of such measures are done by taking the convex linear combinations of MFs between two IFSs. On the basis of such representations, a number of desirable properties of these measures are examined. It is analyzed that the existing divergence measures are distinct cases of the proposed measure; as a result, the proposed measure is with a higher suitability and generalizability.

Recent years, numerous MCDA approaches such as “technique for order of preference by similarity to ideal solution (TOPSIS)”, “visekriterijumska optimizacija i kompromisno resenje (VIKOR)”, “complex proportional assessment (COPRAS)”, “weighted aggregated sum product assessment (WASPAS)”, “evaluation based on distance from average solution (EDAS)” and others have been commenced to cope the realistic MCDA problems. While employing these approaches in solving MCDA problems, the ranking outcomes produced by the TOPSIS, VIKOR, COPRAS, WASPAS and EDAS may alter significantly in accordance with the variation of weight distributions of attributes (Batool et al., 2021; Rudnik et al., 2021, Mishra et al., 2022b,c). Alternatively, the dependability and permanence of the outcomes obtained by these approaches are inadequate (Wen et al., 2019). To conquer this inadequacy, Yazdani et al. (Yazdani et al., 2019a) presented an MCDA method, named as CoCoSo model, which unites the aggregation of compromise value with different models to find a “compromise solution (CS)”. The CoCoSo model is a combination of “weighted sum model (WSM)” and “exponentially weighted product model (EWPM)”. Yazdani et al. (2019b) gave an integrated tool with the “decision making trial and evaluation laboratory (DEMATEL)” and “best-worst method (BWM)” with CoCoSo method to choose suitable supplier. Rani and Mishra (2020) presented a CoCoSo model for the evaluation of “sustainable waste electrical and electronics equipment (SWEEE)” recycling partner with “single-valued neutrosophic sets (SVNSs)”. Tavana et al. (2021) combined the fuzzy BWM and CoCoSo methods with Bonferroni functions for assessing and prioritizing the suppliers in reverse supply chains. Mishra and Rani (2021) designed a model by combining the CoCoSo and CRITIC approaches under the context of SVNSs to solve the 3PRLPs assessment problem. Bai et al. (2022) discussed a new decision-making methodology based on the q-rung orthopair fuzzy SWARA and CoCoSo methods to assess the “sustainable circular supply chain (SCSC)” risks in manufacturing firm. Narang et al. (2022) studied an integrated decision support system based on generalized heronian operator and CoCoSo method, and applied for portfolio analysis. Mishra et al. (2022a) combined the Archimedean copula operator with the CoCoSo model for the assessment of smart cities to adopt “internet of things barriers (IoTBs)” on “Fermatean fuzzy sets (FFSs)”.

Accordingly, the present study has a three-folded objective. First, a new method proposes to select, rank and evaluate the significant therapy for patients based on multiple criteria. Second, a novel MCDM method is developed based on the CoCoSo and IFSs named as IF-CoCoSo approach. Recently, Yazdani et al. (2019a) introduced the novel CoCoSo approach with the aid of some aggregation strategies. The use of the CoCoSo is limited within the context of IFSs. Thus, we present the CoCoSo to handle the medical decision making issues based on IFSs.

In summary, the current work has the following contributions:

- To propose an innovative “generalized score function (GSF)” and divergence measures to determine the criteria weights.
- To introduce an innovative GSF by considering the “hesitancy degree (HD)” that exists between the MF and NF of IFNs.
- To present two new parametric divergence measures of order α and β represented as class of α and (α, β) for IFSs.
- To introduce an algorithm for IF-CoCoSo method based the CoCoSo approach and IFSs.

- To make clear how applicable and reliable is the proposed IF-CoCoSo approach, an application of therapy selection problem for patients is discussed.

The rest part of this study is presented in the following way: An extensive literature review on fuzzy MCDM approaches in healthcare sciences is provided in Section 2. Section 3 discusses the preliminaries related to the IFSs, new GSF and parametric divergence measures for IFSs. Section 4 introduces the IF-CoCoSo method with the GSF and parametric divergence measures. Section 5 discusses a case study for medical decision making using IFSs, which illustrates the feasibility of the proposed method. Section 5 shows the comparative and sensitivity analyses to illustrate the utility of the presented method. Section 7 focuses on the conclusion, limitations, and future recommendations.

## 2.Application of fuzzy MCDM models in medical problems

In the context of decision analysis, MCDM provides a systematic way for the assessment of options/cases/alternatives over a set of pre-determined selected criteria. IFSs have gained much interest from authors in medical MCDM. Szmidt & Kacprzyk (2004) provided an application of medical MCDM based on the distance measures between IFSs. Vlachos & Sergiadis (2007) attempted to extend the approach proposed by Szmidt & Kacprzyk (2001) through taking into consideration a new measure based on symmetric discrimination information. The two IFS-based applications developed in the biomedicine field are the classification of bacteria by Khatibi & Montazer (2009) and the medical image segmentation (Chaira, 2014). Nowadays, numerous MCDM methods are effectively employed to help medical MCDM in FSs and IFSs contexts. Hsieh et al. (2018) integrated "analytic hierarchy process (AHP)" and fuzzy TOPSIS to assess the important parameters of human errors in emergency sections. Honarbakhsh et al. (2018) employed the AHP to assess the "respiratory protection program (RPP)" in teaching hospitals under FSs. According to findings of the present study, the most proper option for ambulance location is road network. Xiao (2018) proposed a fuzzy MCDM called D-number to assess the "healthcare waste treatment (HWT)" technologies.

In addition various of previous studies used the classical MCDM method to evaluate the healthcare management topics, for example; a novel approach developed by Malekpoor et al. (2022) was on the basis of TOPSIS and "case based reasoning (CBR)" to optimize dose planning procedure for minimizing the concerning prostate cancer. Bahadori et al. (2018) integrated the "grey relational analysis (GRA)" and VIKOR models to assess the "quality control effectiveness (QCE)" in hospitals. Kirkire et al. (2018) introduced a model using the SEM-TOPSIS for prioritizing the risk factors of medical devices. Rani et al. (2020) presented the Pythagorean fuzzy-COPRAS approach to treat the "pharmacological therapy selection" for "type 2 diabetes (T2D)" problem. Liu et al. (2021) presented and ranked the "medical waste treatment technologies (MWTTs)" through the CoCoSo method on "Pythagorean fuzzy sets (PFSs)".

## 3. Concepts related to the proposed approach

This section firstly presents the basic concepts of IFSs and then proposes generalized score function and divergence measure under intuitionistic fuzzy environment.

### 3.1. Preliminaries

This section concentrates on the demonstration of the decision information based on IFSs. In the following step, this study focuses on the aggregation based on the IF-CoCoSo method.

In the FSs doctrine, the MF of an element is represented based on the interval number of [0, 1], whereas the NF essentially is complemented. Though, in concern, this hypothesis does not meet with human opinions. Hence, Atanassov (1986) defined the IFSs as follows:

**Definition 1.** Atanassov (1986) defined the mathematical form of an IFS '*S*' on $\Lambda = \{w_1, w_2, \ldots, w_t\}$ as

$$S = \{\langle w_k, \mu_S(w_k), \nu_S(w_k)\rangle : w_k \in \Lambda\}, \tag{1}$$

wherein $\mu_S : \Lambda \to [0, 1]$ and $\nu_S : \Lambda \to [0, 1]$ show the MF and NF of $w_k$ to *S* in $\Lambda$, respectively, with the condition

$$\begin{aligned} &0 \le \mu_S(w_k) \le 1,\ 0 \le \nu_S(w_k) \le 1, \\ &0 \le \mu_S(w_k) + \nu_S(w_k) \le 1,\ \forall\, w_k \in \Lambda. \end{aligned} \tag{2}$$

The intuitionistic index of an element $w_k \in \Lambda$ to *S* is defined by

$$\pi_S(w_k) = 1 - \mu_S(w_k) - \nu_S(w_k) \text{ and } 0 \le \pi_S(w_k) \le 1,\ \forall\, w_k \in \Lambda.$$

Next, Xu (2007) described this term $\langle \mu_S(w_k), \nu_S(w_k)\rangle$ as an "intuitionistic fuzzy number (IFN)", denoted by $\tau = (\mu_\tau, \nu_\tau)$, which satisfies $\mu_\tau, \nu_\tau \in [0,1]$ and $0 \le \mu_\tau + \nu_\tau \le 1.$

**Definition 2** (Xu, 2007). Consider $\tau_k = (\mu_k, \nu_k),\ j = 1, 2, \ldots, t$ be the IFNs. Then

$$\mathbb{S}(\tau_k) = (\mu_k - \nu_k) \text{ and } \hbar(\tau_k) = (\mu_k + \nu_k). \tag{3}$$

are the score and accuracy functions, respectively.

**Definition 3** (Xu, 2007). Let $\tau_k = (\mu_k, \nu_k),\ j = 1, 2, \ldots, t$ be the IFNs. Then the "intuitionistic fuzzy weighted average (IFWA)" and "intuitionistic fuzzy weighted geometric (IFWG)" operators are given by

$$IFWA_\psi(\tau_1, \tau_2, \ldots, \tau_t) = \bigoplus_{k=1}^{t} w_k\, \tau_k = \left[1 - \prod_{k=1}^{t}(1-\mu_k)^{\psi_k}, \prod_{k=1}^{t} \nu_k^{w_k}\right], \tag{4}$$

$$IFWG_\psi(\tau_1, \tau_2, \ldots, \tau_t) = \bigotimes_{k=1}^{t} w_k\, \tau_k = \left[\prod_{k=1}^{t} \mu_k^{\psi_k}, 1 - \prod_{k=1}^{t}(1-\nu_k)^{\psi_k}\right], \tag{5}$$

where $\psi_k = (\psi_1, \psi_2, \ldots, \psi_t)^T$ is a weight vector of $\tau_k,\ k = 1, 2, \cdots, t$ with $\sum_{k=1}^{t} \psi_k = 1$ and $\psi_k \in [0, 1]$.

The divergence measure of IFSs is a tool for calculating the amount of difference between IFSs. Vlachos and Sergiadis (2007) firstly gave the formula for IF-divergence measure. Further, Montes et al. (2015) defined the new axiomatic definition of IF-divergence measure, which as

**Definition 4** (Montes et al., 2015). Let $S, T \in IFSs(\Lambda)$. Then $J: IFSs(\Lambda) \times IFSs(\Lambda) \to \mathbb{R}$ is a divergence measure, if it fulfills the following postulates:

(D1). $J(S,T) = J(T,S)$;

(D2). $J(S,T) = 0$ if and only if $S = T$;

(D3). $J(S \cap U, T \cap U) \leq J(S,T)$, for every $U \in IFS(\Lambda)$;

(D4). $J(S \cup U, T \cup U) \leq J(S,T)$, for every $U \in IFS(\Lambda)$.

### 3.2. Generalized score function and divergence measure under IFSs context

In the present section, a new generalized score function and divergence measures are introduced for IFSs.

#### *3.2.1. Generalized score function (GSF)*

In this subsection, a new GSF is developed by taking the “hesitancy degree (HD)” between the MFs and NFs of IFNs.

**Definition 5.** Suppose $\tau_k = (\mu_k, \nu_k)$, $k = 1, 2, \cdots, t$ be the IFNs. A GSF of an IFN is given by

$$\mathbb{S}^*(\tau_k) = \mu_k \left[1 + (\varepsilon_1 + \varepsilon_2)(1 - \mu_k - \nu_k)\right], \tag{6}$$

where $\varepsilon_1 + \varepsilon_2 = 1$, $\varepsilon_1, \varepsilon_2 > 0$ denotes the attitudinal behaviors of the proposed function, showing the degree of weighted average of the HD between the MF and NF of IFNs.

When $\varepsilon_1 = \varepsilon_2 = \frac{1}{2}$, the GSF is decreased to the score function proposed by Liu and Wang (2007).

**Theorem 1.** Let $\tau_k = (\mu_k, \nu_k)$, $k = 1, 2$ be two IFNs and $\mathbb{S}^*(.)$ be a GSF. Then $\mathbb{S}^*(.)$ holds the properties as follows:

(s1) For any IFN, $\mathbb{S}^*(\tau_k) \in [0,1]$;

(s2) $\mathbb{S}^*((0,1)) = 0$, $\mathbb{S}^*((1,0)) = 1$;

(s3) If $\mathbb{S}^*(\tau_1) > \mathbb{S}^*(\tau_2)$, then $\mathbb{S}^*(\tau_1^c) < \mathbb{S}^*(\tau_2^c)$;

(s4) For a fuzzy subset $\tau_k = (\mu_k, 1 - \mu_k)$, $\mathbb{S}^*(\tau_k) = \mu_k$;

(s5) If $(\mu_1 - \nu_1) - (\mu_2 - \nu_2) > 0$ and $(\mu_1 + \nu_1) - (\mu_2 + \nu_2) > 0$, then $\mathbb{S}^*(\tau_1) > \mathbb{S}^*(\tau_2)$;

(s6) If $(\mu_1 - \nu_1) - (\mu_2 - \nu_2) < 0$ and $(\mu_1 + \nu_1) - (\mu_2 + \nu_2) < 0$, then $\mathbb{S}^*(\tau_1) < \mathbb{S}^*(\tau_2)$.

**Proof:** The proof is omitted.

Figure 1 depicts the score value of $\mathbb{S}^*(\tau_k)(\varepsilon_1 + \varepsilon_2 = 1, \varepsilon_1, \varepsilon_2 > 0)$ when $(\mu_k, \nu_k) = (0.1, 0.7)$ and $(\mu_k, \nu_k) = (0.6, 0.2)$. The color of each point $(\varepsilon_1, \varepsilon_2)$ on the simplex illustrates the entropy of the fixed IFNs. As the value of $\varepsilon_1$ and $\varepsilon_2$ become bigger, the value of $\mathbb{S}^*(\tau_k)$ becomes bigger.

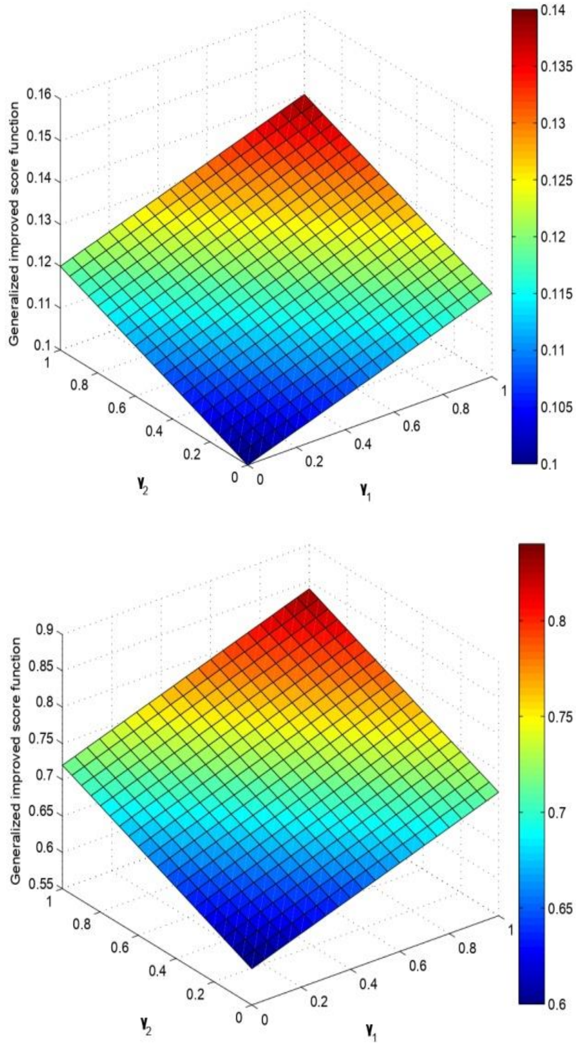


**Figure 1.** GSF $\mathbb{S}^*(\tau_k)$ with respect to parameters $\varepsilon_1, \varepsilon_2 \in [0,1]$, (a) when $(\mu_k, \nu_k) = (0.1, 0.7)$ (b) when $(\mu_k, \nu_k) = (0.6, 0.2)$

*3.2.2. Parametric divergence measures for IFSs*

Here, we present two novel generalizable parametric divergence measures of order α and β denoted as class of α and (α,β). A number of favored properties are also taken into account.

Corresponding to the divergence measure introduced by Parkash and Kumar (2011), we introduce a parametric divergence measure as follows:

$$CE_\alpha(S,T) = \frac{1}{t\left(\left(\alpha - 1/2\right)^{\ln 2} - 1\right)} \sum_{k=1}^{t} \left[ \mu_S(w_k)\left(\alpha - 1/2\right)^{\ln\left(\frac{2\mu_S(w_k)}{\mu_S(w_k)+\mu_T(w_k)}\right)} \right. \tag{7}$$

$$+\nu_S(w_k)(\alpha-1/2)^{\ln\left(\frac{2\nu_S(w_k)}{\nu_S(w_k)+\nu_T(w_k)}\right)}+\pi_S(w_k)(\alpha-1/2)^{\ln\left(\frac{2\pi_S(w_k)}{\pi_S(w_k)+\pi_T(w_k)}\right)}-1\Bigg],$$

where $\alpha > \frac{1}{2}$ and $\alpha \neq \frac{1}{2}$.

Since Eq. (7) is not symmetric, we define the symmetric version as follows:

$$J_1(S,T) = CE_\alpha(S\parallel T)+CE_\alpha(T\parallel S). \tag{8}$$

Next, we introduce a Biparametric IF-divergence measure as

$$CE_2(S\parallel T)=\frac{1}{t\left(\left(\frac{\alpha-\beta}{2\beta}\right)^{\ln 2}-1\right)}\sum_{k=1}^{t}\Bigg[\mu_S(w_k)\left(\frac{\alpha}{2\beta}-\frac{1}{2}\right)^{\ln\left(\frac{2\mu_S(w_k)}{\mu_S(w_k)+\mu_T(w_k)}\right)} \tag{9}$$

$$+\nu_S(w_k)\left(\frac{\alpha}{2\beta}-\frac{1}{2}\right)^{\ln\left(\frac{2\nu_S(w_k)}{\nu_S(w_k)+\nu_T(w_k)}\right)}+\pi_S(w_k)\left(\frac{\alpha}{2\beta}-\frac{1}{2}\right)^{\ln\left(\frac{2\pi_S(w_k)}{\pi_S(w_k)+\pi_T(w_k)}\right)}-1\Bigg],$$

where $\alpha > \beta$ and $\alpha \neq \beta$.

Here, Eq. (9) is not symmetric. Thus, the symmetric measure is given by

$$J_2(S,T) = CE_\alpha^\beta(S\parallel T)+CE_\alpha^\beta(T\parallel S).$$

(10)

**Theorem 2.** Let $S,T,U \in IFSs(\Lambda)$. Then, the measure $J_\gamma(S,T);\ \gamma=1,2,$ shown in Eqns. (8) and (10), satisfies.

(P1) $J_\gamma(S,T)=J_\gamma(T,S)$,

(P2) $0 \le J_\gamma(S,T) \le 1$, $J_\gamma(S,S^c)=1$ if and only if $S \in P(\Lambda)$, where $P(\Lambda)$ is the set of all crisp sets,

(P3) $J_\gamma(S,T)=0$ iff $S=T$,

(P4) $J_\gamma(S,T)=J_\gamma(S^c,T^c)$ and $J_\gamma(S^c,T)=J_\gamma(S,T^c)$,

(P5) $J_\gamma(S,T)\le J_\gamma(S,U)$ and $J_\gamma(T,U)\le J_\gamma(S,U)$, for $S\subseteq T\subseteq U$,

(P6) $J_\gamma(S\cup T, S\cap T)=J_\gamma(S,T)$,

(P7) $J_\gamma(S\cup T,U)\le J_\gamma(S,U)+J_\gamma(T,U)$, $\forall U\in IFS(\Lambda)$,

(P8) $J_\gamma(S\cap T,U)\le J_\gamma(S,U)+J_\gamma(T,U)$, $\forall U\in IFS(\Lambda)$,

(P9) $J_\gamma(S\cap U, T\cap U)\le J_\gamma(S,T)$ for every $U\in IFS(\Lambda)$,

(P10) $J_\gamma(S\cup U, T\cup U)\le J_\gamma(S,T)$ for every $U\in IFS(\Lambda)$.

**Proof:** Properties (P1) - (P4) and (P6) - (P8) are easily proved from the definition. Hence, we omit the proof.

(P5) Let $S\subseteq T\subseteq U$. Then $\mu_S\le\mu_T\le\mu_U$ and $\nu_S\ge\nu_T\ge\nu_U$. It implies

$$|\mu_S-\mu_T|+|\nu_S-\nu_T|+|\pi_S-\pi_T|\le|\mu_S-\mu_U|+|\nu_S-\nu_U|+|\pi_S-\pi_U|,$$

$$|\mu_T-\mu_U|+|\nu_T-\nu_U|+|\pi_T-\pi_U|\le|\mu_S-\mu_U|+|\nu_S-\nu_U|+|\pi_S-\pi_U|,$$

therefore, $J_\gamma(S,T)\le J_\gamma(S,U)$ and $J_\gamma(T,U)\le J_\gamma(S,U)$.

To prove (P9) and (P10), the fixed set $\Lambda$ is partitioned into 8 subsets as follows:

$$\Lambda = \{w_k \in \Lambda \mid S(w_k) \le T(w_k) = U(w_k)\} \cup \{w_k \in \Lambda \mid S(w_k) = U(w_k) \le T(w_k)\}$$

$$\cup \{w_k \in \Lambda \mid S(w_k) \le T(w_k) < U(w_k)\} \cup \{w_k \in \Lambda \mid S(w_k) \le U(w_k) < T(w_k)\}$$

$$\cup \{w_k \in \Lambda \mid T(w_k) < S(w_k) \le U(w_k)\} \cup \{w_k \in \Lambda \mid T(w_k) \le U(w_k) < S(w_k)\}$$

$$\cup \{w_k \in \Lambda \mid U(w_k) < S(w_k) \le T(w_k)\} \cup \{w_k \in \Lambda \mid U(w_k) < T(w_k) < S(w_k)\},$$

which are indicated by $\Psi_1, \Psi_2, \dots, \Psi_8$. Based on Montes et al. (2015), for each $\Psi_j;\ j = 1, 2, \dots, 8,$ we have $\left|(S \cup U)(w_k) - (T \cup U)(w_k)\right| \le \left|S(w_k) - T(w_k)\right|$ and $\left|(S \cap U)(w_k) - (T \cap U)(w_k)\right| \le \left|S(w_k) - T(w_k)\right|$.

Thus, from (P5), we get $J_\gamma(S \cap U, T \cap U) \le J_\gamma(S, T)$ and $J_\gamma(S \cup U, T \cup U) \le J_\gamma(S, T)$ for every $U \in IFS(\Lambda)$.

**Remark 1:** It is interesting to point out that if $\alpha \to 1/2$, then Eq. (7) converts to the divergence measures of IFSs proposed by Wei and Ye (2010). Also, when $\alpha \to 1/2$ and $\pi_S(w_k) = 0 = \pi_T(w_k)$, the proposed divergence given by Eq. (7) converts to measure given by Shang and Jiang (1997). Similarly, the measure $CE_2(S \| T)$ transforms to measure proposed by Wei and Ye (2010) for $\alpha = \beta$ and when $\pi_S(w_k) = 0 = \pi_T(w_k)$ and $\alpha = \beta$, then the proposed divergence shown in Eq. (9) transforms to the measure given by Shang and Jiang (1997).

## 4. Proposed IF-CoCoSo method

The present section aims at the development of an extended CoCoSo approach for the purpose of handling the MCDM issues on IFSs. The presented method extends the method given in Yazdani et al. (2019a). In MCDM process, consider a discrete set of *m* alternatives/options $H = \{H_1, H_2, \dots, H_m\}$ over a set of criteria/attributes $P = \{P_1, P_2, \dots, P_n\}$. Consider a group of "decision makers/experts (DMs/DEs)" $D = \{D_1, D_2, \dots, D_\ell\}$ to make a suitable decision for given alternatives. The procedural steps of IF-CoCoSo method is depicted in the following steps (see Figure 2):

**Step 1:** Create the "Linguistic decision-matrix (LDM)".

Owing to the vagueness of the human mind, lack of data and imprecise knowledge about the options, the DEs define the LDM to evaluate his/her decision on option $H_i$

concerning a criterion $P_j$. Then, we construct the performance evaluation matrix $Y_k = \left[ y_{ij}^{(r)} \right]_{m\times n}$ for each DM considering the criterion set.

$$Y_k = \left( y_{ij}^{(r)} \right)_{m\times n} = \begin{matrix} \\ H_1 \\ \vdots \\ H_m \end{matrix} \begin{matrix} P_1 & \cdots & P_n . \\ \left[ \begin{matrix} (\mu_{11r}, \nu_{11r}) & \cdots & (\mu_{1nr}, \nu_{1nr}) \\ \vdots & \ddots & \vdots \\ (\mu_{m1r}, \nu_{m1r}) & \cdots & (\mu_{mnr}, \nu_{mnr}) \end{matrix} \right]_{m\times n} \end{matrix}, \quad \forall r. \tag{11}$$

**Step 2:** Obtain the importance of DEs.

The importance ratings of DEs are given as $\xi_r = (\mu_r, \nu_r),\ r = 1, 2, \cdots, \ell.$ For the aim of viewing their relative importance in the MCDM model, the crisp weights of DEs are expressed by Eq. (12).

$$\varpi_r = \frac{\mu_r \left( 2 - \mu_r - \nu_r \right)}{\sum_{r=1}^{\ell} \left[ \mu_r \left( 2 - \mu_r - \nu_r \right) \right]},\ r = 1, 2, \ldots, \ell. \tag{12}$$

**Step 3:** Build an "aggregated intuitionistic fuzzy decision-matrix (A-IF-DM)".

Next, for aggregating all the single opinions and constructing the collective decision matrix, we need to form an A-IF-DM by using IFWA operator. Let $\mathbb{R} = \left[ y_{ij} \right]_{m\times n}$ be the A-IF-DM, where $y_{ij} = \left( \mu_{ij}, \nu_{ij} \right),\ i = 1, 2, \ldots, m,\ j = 1, 2, \ldots, n,$ where

$$y_{ij} = \left\langle 1 - \prod_{r=1}^{\ell} \left( 1 - \mu_{ijr} \right)^{\varpi_r}, \prod_{r=1}^{\ell} \left( \nu_{ijr} \right)^{\varpi_r} \right\rangle. \tag{13}$$

**Step 4:** Create the "normalized aggregated intuitionistic fuzzy decision matrix (NA-IF-DM)".

The NA-IF-DM $M = \left[ \varsigma_{ij} \right]_{m\times n}$ is evaluated and given by

$$\varsigma_{ij} = \begin{cases} y_{ij} = \left( \mu_{ij}, \nu_{ij} \right), & \text{for benefit criterion,} \\ \left( y_{ij} \right)^c = \left( \nu_{ij}, \mu_{ij} \right), & \text{for cost criterion.} \end{cases} \tag{14}$$

**Step 5:** Compute criteria weights.

When attribute weights are completely unknown, then IF-divergence measure-based weight-determining procedure is used to derive the weights of criteria. Thus, the attribute weight is determined as

$$\varphi_j = \frac{\sum_{i=1}^{m} \left[ \frac{1}{m-1} \sum_{t=1, t\neq i}^{m} \left( 1 - J_\gamma \left( y_{ij}, y_{tj} \right) \right) + \mathbb{S}^* \left( y_{ij} \right) \right]}{\sum_{j=1}^{n} \left( \sum_{i=1}^{m} \left[ \frac{1}{m-1} \sum_{t=1, t\neq i}^{m} \left( 1 - J_\gamma \left( y_{ij}, y_{tj} \right) \right) + \mathbb{S}^* \left( y_{ij} \right) \right] \right)},\ \forall j. \tag{15}$$

**Step 6:** Calculate the WSM and EWPM.

The WSM $\left(\wp_i^{(1)}\right)$ value for each option is calculated using the IFWA operator as

$$\wp_i^{(1)} = \overset{n}{\underset{j=1}{\oplus}} \varphi_j \, \varsigma_{ij}. \tag{16}$$

The EWPM $\left(\wp_i^{(2)}\right)$ value for each alternative is computed using the IFWG operator as

$$\wp_i^{(2)} = \overset{n}{\underset{j=1}{\otimes}} \varphi_j \, \varsigma_{ij}. \tag{17}$$

**Step 7:** Calculate the "balanced compromise scores (BCSs)" of each option.

Here, the following procedures are applied to find the of alternatives, which are derived as

$$Q_i^{(1)} = \frac{\mathbb{S}^*\left(\wp_i^{(1)}\right) + \mathbb{S}^*\left(\wp_i^{(2)}\right)}{\sum_{i=1}^{m}\left(\mathbb{S}^*\left(\wp_i^{(1)}\right) + \mathbb{S}^*\left(\wp_i^{(2)}\right)\right)}, \tag{18}$$

$$Q_i^{(2)} = \frac{\mathbb{S}^*\left(\wp_i^{(1)}\right)}{\min_i \mathbb{S}^*\left(\wp_i^{(1)}\right)} + \frac{\mathbb{S}^*\left(\wp_i^{(2)}\right)}{\min_i \mathbb{S}^*\left(\wp_i^{(2)}\right)}, \tag{19}$$

$$Q_i^{(3)} = \frac{\vartheta \mathbb{S}^*\left(\wp_i^{(1)}\right) + (1-\vartheta)\mathbb{S}^*\left(\wp_i^{(2)}\right)}{\vartheta \max_i \mathbb{S}^*\left(\wp_i^{(1)}\right) + (1-\vartheta)\max_i \mathbb{S}^*\left(\wp_i^{(2)}\right)}, \tag{20}$$

where $\vartheta$ is a strategic coefficient and $\vartheta \in [0,1]$. Generally, we take $\vartheta = 0.5$.

**Step 8:** Find the "overall compromise solution (OCS)" of alternatives.

The OCS $\left(\mathbb{Q}_i\right)$ of each option is determined by

$$Q_i = \left(Q_i^{(1)} Q_i^{(2)} Q_i^{(3)}\right)^{1/3} + \frac{1}{3}\left(Q_i^{(1)} + Q_i^{(2)} + Q_i^{(3)}\right). \tag{21}$$

To end, prioritize the options by arranging the OCS $(Q_i)$ in descending order.

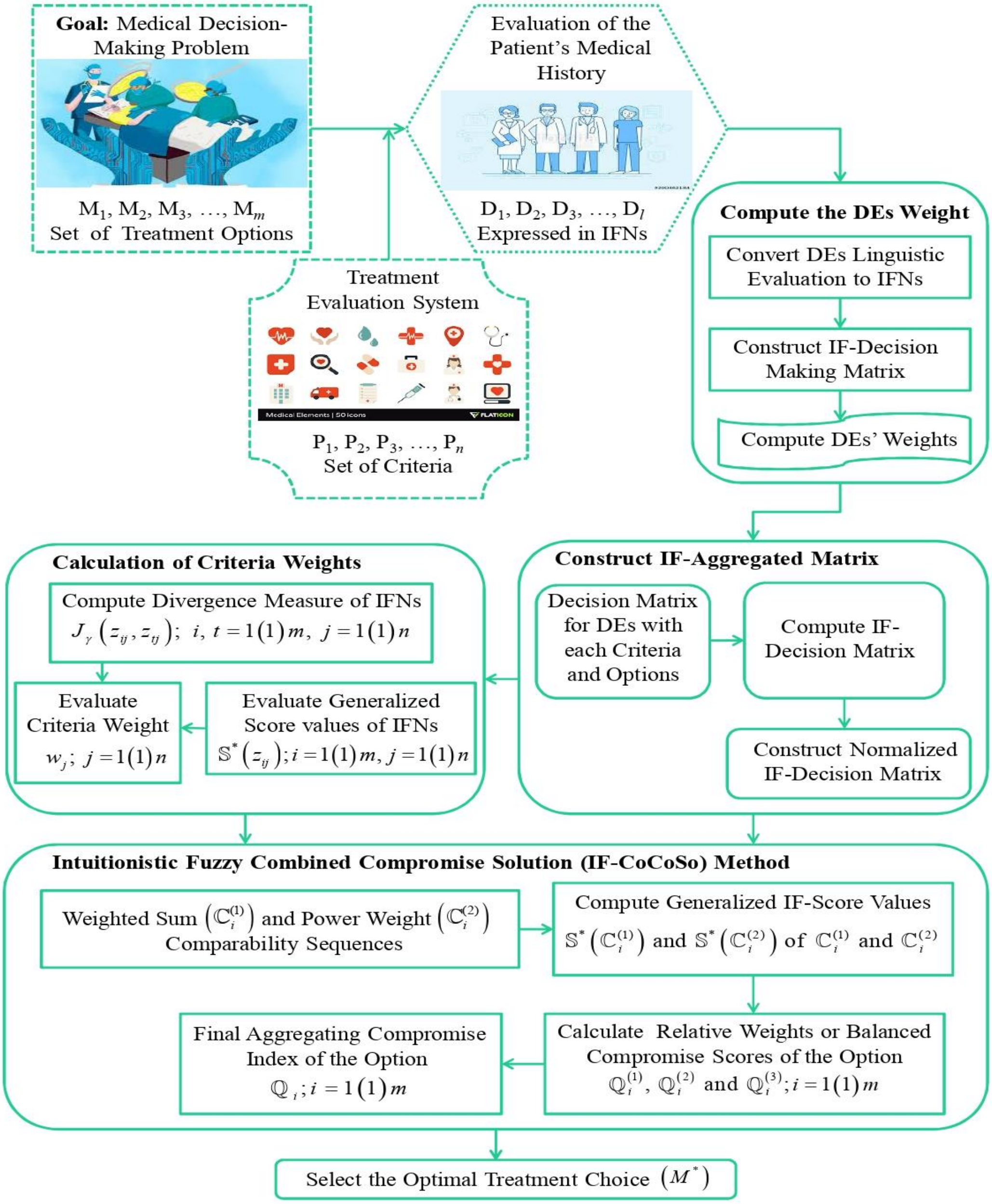


**Figure 2.** Flowchart of the IF-CoCoSo method

## 5. Application of proposed method in medical decision-making

In the healthcare system, MCDM regarding the patient healthcare structure is more complicated in compared to decision making procedure based on individual case because of multiple DMs such as the patients, the families of patients and healthcare personnel. In the patient-centered healthcare system, there is a requirement to adopt group decision making techniques involving family opinions, patient inclinations and professional judgments by medical personnel and team. The subjects and perspectives of group decision making are combined for evaluating the patient healthcare problems. The patient-centered care is a healthcare system which provides preferences and needs of patients as well as the autonomous of the patients to decide for care and treatment of themselves (Pelzang, 2010; Greene et al., 2012). Therefore, patient-centered care considers the relatives and patients are experienced to choose their own expectations and needs and they are eligible to take decisions and select their preferences. However, involving patients, relatives, and professional medical decision-makers to provide the decision information is basically vague and contains numerous uncertainties.

The case study was from the department of neurosurgery, New Delhi in India. “Multiple sclerosis (MS)” is more and more identified in India because of the increase in the number of practicing neurologists and affordable and easy availability of “magnetic resonance imaging (MRI)”. An MS is an “autoimmune inflammatory demyelinating illness (AIDI)” of the “central nervous system (CNS)”. In India, the illness came to be identified in the 1960s. Retrospective analysis with longitudinal follow-up of patients mentioned to a single tertiary healthcare center with neurology services in the neurosurgery department - New Delhi in India.

For this study, we selected a 55-year-old male with his relatives. A physician evaluated the medical history of the patient and his current physical situation by providing three kinds of treatments, including rehabilitation ($H_1$), corticosteroids ($H_2$), and plasma exchange (plasmapheresis) ($H_3$). To help the male patient and his relatives for understanding the disadvantages and advantages of each treatment option, the physician presents the related information based on various evaluation criteria, including related cost, probability of a recurrence, discomfort index of the treatment, survival rate, probability of a cure, number of days of hospitalization, self-care capacity, severity of the complications and severity of the side effects. The physician requested the patient and his relatives to discuss and evaluate the different kinds of treatment options thoroughly.

In the following stage, the best treatment option is determined with the help of proposed IF-CoCoSo approach. For doing so, three DMs assessed the treatment options over the evaluative criteria, which are classified based on benefit/cost criteria. Here, the criteria $P_1$, $P_3$ and $P_9$ are determined as the benefit types, and rest are determined as the cost types of criteria. Based on the above discussion and current literature review of the medical decision making, several criteria have identified and provided in Table 1.

**Table 1:** Important criteria for medical decision making in the literature review.

| Name of Criteria | Symbol | Reference source |
|---|---|---|
| Survival rate | $P_1$ | Chen (2015); Chen et al. (2013); Hu et al. (2019a); Chen (2017); Chen (2013); Hu et al. (2019b) |
| Severity of the side effects | $P_2$ | Chen (2015); Ma et al. (2017); Chen et al. (2013); Chen (2017); Huet al. (2019b); Chen (2013); Li et al. (2018) |
| Probability of a cure | $P_3$ | Chen (2015); Chen et al. (2013); Hu et al. (2019a); Chen (2017); Chen (2013); Hu et al. (2019b); Li et al. (2018) |
| Severity of the complications | $P_4$ | Chen (2015); Chen et al. (2013); Chen (2017); Chen (2013); Li et al. (2018) |
| Discomfort index of the treatment | $P_5$ | Chen (2015); Hu et al. (2019b); Chen et al. (2013); Chen (2017); Hu et al. (2019c); Chen (2013); Li et al. (2018) |
| Cost/expense | $P_6$ | Chen (2015); Chen et al. (2013); Ma et al. (2017); Chen (2017); Hu et al. (2019a); Chen (2013); Hu et al. (2019b); Li et al. (2018) |
| Number of days of hospitalization | $P_7$ | Chen (2015); Hu et al. (2019a); Chen et al. (2013); Chen (2017);Hu et al. (2019c); Chen (2013); Li et al. (2018) |
| Probability of a recurrence | $P_8$ | Chen (2015); Ma et al. (2017); Chen et al. (2013); Chen (2017); Hu et al. (2019a); Chen (2013); Hu et al. (2019c); Li et al. (2018) |
| Self-care capacity | $P_9$ | Chen (2015); Chen (2017); Chen (2013); Hu et al. (2019c); Hu et al. (2019b); Li et al. (2018) |

The LVs and corresponding IFNs for the significance of the alternative, DEs and criteria are presented in Tables 2 and 3 adopted from Rani et al., (2021) and Hezam et al. (2022). According to the results of Table 3 and Eq. (12), the weights of DEs are estimated and shown in Table 4.

**Table 2:** The LVs and corresponding IFNs

| LVs | IFNs |
|---|---|
| Extremely unimportant (EU) | (0.1, 0.8, 0.1) |
| Very unimportant (VU) | (0.2, 0.7, 0.1) |
| Quite Unimportant (QU) | (0.3, 0.6, 0.1) |
| Unimportant (U) | (0.4, 0.5, 0.1 ) |
| Neutral (N) | (0.55, 0.4, 0.05) |
| Important(QI) | (0.65, 0.3, 0.05) |
| Important (I) | (0.75 , 0.2, 0.05) |
| Very important (VI) | (0.9, 0.05, 0.05) |
| Extremely important (EI) | (1, 0, 0) |

**Table 3:** The LVs for significance rating DEs'

| LVs | IFNs |
|---|---|
| Outstanding (O) | (1, 0, 0) |
| Exceeds expectations (EE) | (0.9, 0.05, 0.05) |
| Meet expectations (ME) | (0.7,0.2, 0.1) |
| Moderate (M) | (0.6,0.3, 0.1) |
| Needs improvements (NI) | (0.3,0.6, 0.1) |
| Unacceptable (U) | (0.1,0.8, 0.1) |

**Table 4:** Evaluated DEs' weights

| Decision expert (DEs) | $D_1$ | $D_2$ | $D_3$ |
|---|---|---|---|
| LVs | ME | EE | M |
| IFNs | (0.7, 0.2, 0.1) | (0.9, 0.05, 0.05) | (0.6, 0.3, 0.1) |
| Weights | 0.3242 | 0.3979 | 0.2779 |

Next, Tables 5-7 present the significance ratings of option over different attributes for each DE. With the use of Tables 5-7 and Eq. (13), the A-IF-DM is established and presented in Table 8. By Eq. (14) and Table 8, the normalized A-IF-DM can be showed in Table 9.

**Table 5:** Assessment given by DE $D_1$

| $D_1$ | $H_1$ | $H_2$ | $H_3$ |
|---|---|---|---|
| $P_1$ | (0.8100, 0.0750) | (0.7750, 0.1750) | (0.7900, 0.1100) |
| $P_2$ | (0.7250, 0.1750) | (0.7250, 0.1850) | (0.7250, 0.2350) |
| $P_3$ | (0.4250, 0.3150) | (0.5750, 0.3250) | (0.5500, 0.3850) |
| $P_4$ | (0.5750, 0.3750) | (0.7100, 0.1750) | (0.6900, 0.2100) |
| $P_5$ | (0.3650, 0.1800) | (0.5250, 0.4250) | (0.5250, 0.3250) |
| $P_6$ | (0.4950, 0.3500) | (0.5400, 0.3250) | (0.5400, 0.4250) |
| $P_7$ | (0.7950, 0.2000) | (0.7400, 0.1300) | (0.7400, 0.2100) |
| $P_8$ | (0.8100, 0.1250) | (0.7750, 0.1650) | (0.7750,0.1650) |
| $P_9$ | (0.8100, 0.1600) | (0.6550, 0.2250) | (0.6550, 0.2250) |

**Table 6:** Assessment given by DE $D_2$

| $D_2$ | $H_1$ | $H_2$ | $H_3$ |
|---|---|---|---|
| $P_1$ | (0.7300, 0.2250) | (0.8850, 0.0300) | (0.6950, 0.1250) |
| $P_2$ | (0.6900, 0.2300) | (0.8150, 0.1100) | (0.8150, 0.1350) |
| $P_3$ | (0.4000, 0.3100) | (0.5250, 0.4200) | (0.5000, 0.2300) |
| $P_4$ | (0.4750, 0.3150) | (0.6250, 0.2750) | (0.7250, 0.2250) |
| $P_5$ | (0.3750, 0.2250) | (0.5500, 0.3500) | (0.5000, 0.2250) |
| $P_6$ | (0.4250, 0.3250) | (0.5500, 0.3200) | (0.5500, 0.3150) |
| $P_7$ | (0.7250, 0.2250) | (0.7500, 0.1600) | (0.7500, 0.1600) |
| $P_8$ | (0.8000, 0.1250) | (0.7900, 0.1500) | (0.7900, 0.1500) |
| $P_9$ | (0.8250, 0.1100) | (0.6800, 0.2250) | (0.6800, 0.2250) |

**Table 7:** Assessment given by DE $D_3$

| $D_3$ | $H_1$ | $H_2$ | $H_3$ |
|---|---|---|---|
| $P_1$ | (0.8100, 0.1550) | (0.7250, 0.2100) | (0.6100, 0.3150) |
| $P_2$ | (0.7750, 0.1500) | (0.6900, 0.2350) | (0.7250, 0.1750) |
| $P_3$ | (0.4850, 0.3650) | (0.5600, 0.3600) | (0.5600, 0.3700) |
| $P_4$ | (0.4500, 0.4250) | (0.5250, 0.3600) | (0.6250, 0.2250) |
| $P_5$ | (0.3500, 0.2150) | (0.6100, 0.2750) | (0.4750, 0.3250) |
| $P_6$ | (0.4750, 0.3250) | (0.5000, 0.3400) | (0.5000, 0.3600) |
| $P_7$ | (0.8250, 0.1250) | (0.6500, 0.2250) | (0.6500, 0.2250) |
| $P_8$ | (0.8500, 0.0300) | (0.7500, 0.1250) | (0.7500, 0.1250) |
| $P_9$ | (0.8400, 0.1250) | (0.6500, 0.2250) | (0.6500, 0.2100) |

**Table 8:** The A-IF-DM $\left(y_{ij}\right)_{3\times 9}$ given by DEs

| | $H_1$ | $H_2$ | $H_3$ |
|---|---|---|---|
| $P_1$ | (0.7910, 0.1169, 0.0921) | (0.8011, 0.0857, 0.1132) | (0.7312, 0.2130, 0.0558) |
| $P_2$ | (0.7250, 0.1942, 0.0808) | (0.7813, 0.1479, 0.0708) | (0.7297, 0.1872, 0.0831) |
| $P_3$ | (0.5237, 0.3372, 0.1390) | (0.4803, 0.3220, 0.1978) | (0.5370, 0.3644, 0.0987) |
| $P_4$ | (0.6656, 0.2357, 0.0987) | (0.6163, 0.2718, 0.1119) | (0.5335, 0.3334, 0.1331) |
| $P_5$ | (0.4781, 0.2986, 0.2233) | (0.4846, 0.2682, 0.2472) | (0.5001, 0.2660, 0.2339) |
| $P_6$ | (0.5259, 0.3587, 0.1155) | (0.5128, 0.3202, 0.1670) | (0.4920, 0.3404, 0.1675) |
| $P_7$ | (0.7593, 0.1708, 0.0699) | (0.7422, 0.1787, 0.0791) | (0.7204, 0.1860, 0.0936) |
| $P_8$ | (0.7870, 0.1508, 0.0622) | (0.7933, 0.1414, 0.0653) | (0.7882, 0.0787, 0.1331) |
| $P_9$ | (0.7157, 0.2015, 0.0829) | (0.7369, 0.1784, 0.0847) | (0.7284, 0.1824, 0.0891) |

**Table 9:** Normalized A-IF-DM $\left(\varsigma_{ij}\right)_{3\times 9}$

| | $H_1$ | $H_2$ | $H_3$ |
|---|---|---|---|
| $P_1$ | (0.7910, 0.1169, 0.0921) | (0.8011, 0.0857, 0.1132) | (0.7312, 0.2130, 0.0558) |
| $P_2$ | (0.1942, 0.7250, 0.0808) | (0.1479, 0.7813, 0.0708) | (0.1872, 0.7297, 0.0831) |
| $P_3$ | (0.5237, 0.3372, 0.1390) | (0.4803, 0.3220, 0.1978) | (0.5370, 0.3644, 0.0987) |
| $P_4$ | (0.2357, 0.6656, 0.0987) | (0.2718, 0.6163, 0.1119) | (0.3334, 0.5335, 0.1331) |
| $P_5$ | (0.2986, 0.4781, 0.2233) | (0.2682, 0.4846, 0.2472) | (0.2660, 0.5001, 0.2339) |

| | | | |
|---|---|---|---|
| $P_6$ | (0.3587, 0.5259, 0.1155) | (0.3202, 0.5128, 0.1670) | (0.3404, 0.4920, 0.1675) |
| $P_7$ | (0.1708, 0.7593, 0.0699) | (0.1787, 0.7422, 0.0791) | (0.1860, 0.7204, 0.0936) |
| $P_8$ | (0.1508, 0.7870, 0.0622) | (0.1414, 0.7933, 0.0653) | (0.0787, 0.7882, 0.1331) |
| $P_9$ | (0.7157, 0.2015, 0.0829) | (0.7369, 0.1784, 0.0847) | (0.7284, 0.1824, 0.0891) |

Based on Table 8 and Eq. (15), the criteria weights using the proposed parametric divergence measure and GSF is derived and presented as

$$\varphi_j = (0.1245, 0.1210, 0.0935, 0.1043, 0.0960, 0.0938, 0.1207, 0.1269, 0.1193)^T. \quad (22)$$

Using Table 9 and Eqs (16) and (17), $\wp_i^{(1)}$ and $\wp_i^{(2)}$ with their score values $\mathbb{S}^*(\wp_i^{(1)})$ and $\mathbb{S}^*(\wp_i^{(2)})$ are determined and depicted in Table 10. According to Eqs (18)-(20), the relative weights or balanced compromise scores $Q_i^{(1)}$, $Q_i^{(2)}$ and $Q_i^{(3)}(\vartheta)$ (with $\vartheta = 0.0, 0.2, 0.5, 0.8, 1)$ is computed and given in Table 9, where the compromise decision mechanism coefficient $\vartheta \in [0,1]$. Further, the aggregated compromise index $Q_i(\vartheta)$ (with $\vartheta = 0.5$) of the treatment choice is evaluated and presented in Table 10. From Table 10, $H_2$ is the best treatment choice and $H_1$ is the least favorable option.

**Table 10:** The OCS for each option

| | $\wp_i^{(1)}$ | $\wp_i^{(2)}$ | $\mathbb{S}^*(\wp_i^{(1)})$ | $\mathbb{S}^*(\wp_i^{(2)})$ | $Q_i^{(1)}$ | $Q_i^{(2)}$ | $Q_i^{(3)}(\vartheta)$ | $Q_i(\vartheta)$ |
|---|---|---|---|---|---|---|---|---|
| $H_1$ | (0.4443, 0.4334) | (0.3185, 0.5734) | 0.4986 | 0.3529 | 0.3372 | 2.0678 | 0.9890 | 2.0073 |
| $H_2$ | (0.4419, 0.4084) | (0.3045, 0.5724) | 0.5081 | 0.3420 | 0.3366 | 2.0557 | 0.9873 | 2.0148 |
| $H_3$ | (0.4302, 0.4509) | (0.2994, 0.5573) | 0.4813 | 0.3423 | 0.3262 | 2.0009 | 0.9566 | 1.9492 |

Also, we demonstrate a sensitivity analysis based on various decision-making coefficient values. The value of $\vartheta$ = 0.5 is preferred to be analyzed. The variations of $\vartheta$ aid us in the evaluation of the approach's sensitivity to the movement from the weighted sum comparability sequence, power weight comparability sequence, balanced compromise scores and aggregating compromise index. The results are depicted in Figure 3. Hence, it is clearly recognizable that the presented method has high stability with various values of the parameter $\vartheta$ (0.0, 0.2, 0.5, 0.8 and 1.0). Thus, we can conclude that the presented combination results in enhancing the solidity of the developed method.

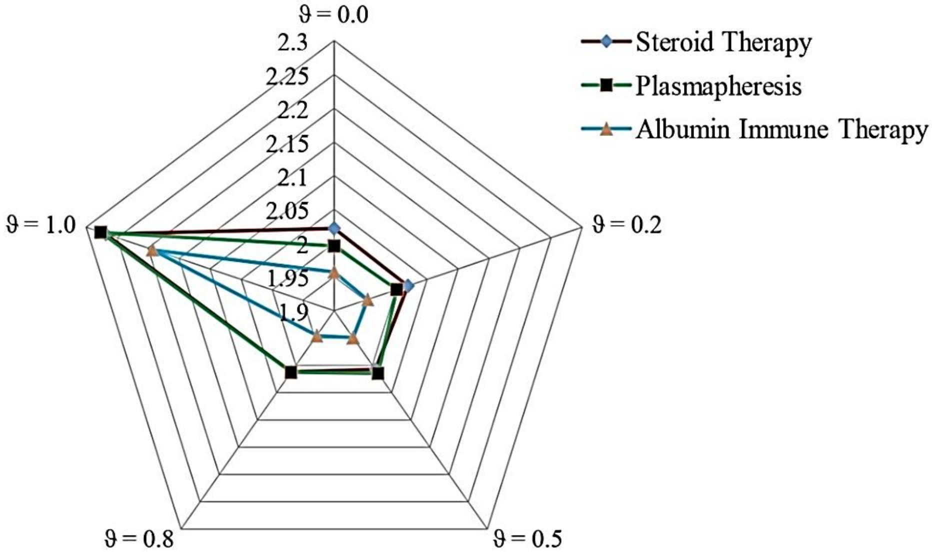


**Figure 3.** Ranking orders of options with strategic coefficient $\vartheta$

## 6. Comparative analyses

Here, a comparison is made between the outcomes achieved from the IF-CoCoSo model and other existing approaches. To show the utility of the IF-CoCoSo method, the IF-TOPSIS method (Joshi and Kumar (2014), IF-VIKOR method (Luo and Wang, 2017) and IF-WASPAS method (Mishra et al., 2019) are used to handle the given case study.

### 6.1. IF-WASPAS model

The IF-WASPAS framework (Mishra et al., 2019) comprises the following procedures:

**Steps 1-7:** Follow the steps of IF-CoCoSo.

**Step 8:** Estimate the WASPAS degree of each alternative as follows:

$$Q_i = \hbar\,\wp_i^{(1)} + \left(1-\hbar\right)\wp_i^{(2)}, \tag{23}$$

where $\hbar$ signifies the strategic coefficient, where $\hbar \in [0,1]$.

**Step 9:** Prioritize the option(s) based on the score values of $Q_i$.

Subsequently, the results of the IF-WASPAS model are demonstrated in Table 11.

**Table 11:** The WASPAS degree of each option using IF-WASPAS method

| Alternative | $\wp_i^{(1)}$ | $\wp_i^{(2)}$ | $\mathbb{S}^*\left(\wp_i^{(1)}\right)$ | $\mathbb{S}^*\left(\wp_i^{(2)}\right)$ | $Q_i\left(\hbar\right)$ | Ranking Order |
|---|---|---|---|---|---|---|
| $H_1$ | (0.4443, 0.4334) | (0.3185, 0.5734) | 0.4986 | 0.3529 | 0.4251 | 2 |
| $H_2$ | (0.4419, 0.4084) | (0.3045, 0.5724) | 0.5081 | 0.3420 | 0.4257 | 1 |
| $H_3$ | (0.4302, 0.4509) | (0.2994, 0.5573) | 0.4813 | 0.3423 | 0.4118 | 3 |

The prioritization of treatment choices is $H_2 \succ H_1 \succ H_3$ and the alternative $H_2$ has the maximum degree of suitability for treatment choice. Next, a sensitivity analysis is presented, which is accompanied with five sets of various values of parameter $(\hbar)$. The value of $\hbar$ = 0.5 is analyzed. The variations of $\hbar$ aid us in the evaluation of the method's sensitivity level to the variation from the WSM to the WPM.

### 6.2. IF-TOPSIS model

The IF-TOPSIS method (Joshi and Kumar, 2014) is discussed as

**Steps 1-5:** Similar as the presented method.

**Step 6:** Compute the "Intuitionistic fuzzy ideal solution (IF-IS)" and "Intuitionistic fuzzy anti-ideal solution (IF-AIS)".

Suppose $P_b$ and $P_n$ be the sets of benefit and non-benefit attributes, respectively. Then the IF-IS $\mathrm{N}^+$ and the IF-AIS solution $\mathrm{N}^-$ can be given as

$$\mathrm{N}^+ = \left\{\left(P_j, \left\langle \max_i \mu_{ij} \mid j \in P_b, \min_i \mu_{ij} \mid j \in P_n \right\rangle, \left\langle \min_i \nu_{ij}\ j \in P_b, \max_i \nu_{ij}\ j \in P_n \right\rangle\right) : i = 1, 2, \ldots, m\right\}, \tag{24}$$

$$\mathrm{N}^- = \left\{\left(P_j, \left\langle \min_i \mu_{ij} \mid j \in P_b, \max_i \mu_{ij} \mid j \in P_n \right\rangle, \left\langle \max_i \nu_{ij}\ j \in P_b, \min_i \nu_{ij}\ j \in P_n \right\rangle\right) : i = 1, 2, \ldots, m\right\}. \tag{25}$$

**Step 7:** Calculate the divergences from IF-IS and IF-AIS.

Using Eq. (8), we compute the weighted IF-divergence $J_\gamma\left(H_i, \mathrm{N}^+\right)$ between the options $H_i$, $\forall\, i$ and the IF-IS $\mathrm{N}^+$, and the divergence $J_\gamma\left(H_i, \mathrm{N}^-\right)$ between the options $H_i, \forall\, i$ and the IF-AIS $\mathrm{N}^-$.

**Step 8:** Calculate the relative closeness coefficient (CC).

The relative closeness coefficient of each option considering the intuitionistic fuzzy IS is evaluated by

$$CC_i = \frac{J_\gamma\left(H_i, \mathrm{N}^-\right)}{J_\gamma\left(H_i, \mathrm{N}^-\right) + J_\gamma\left(H_i, \mathrm{N}^+\right)}, \forall i. \tag{26}$$

**Step 9:** Choose the best option with maximum value of $CC_*$ among the values $CC_i;\ i = 1, 2, \ldots, m.$

From Table 8, Eq. (24) and Eq. (25), the IF-IS and IF-AIS are estimated as follows:

$\mathrm{N}^+$ = {(0.8011, 0.0857, 0.1132), (0.1479, 0.7813, 0.0708), (0.5370, 0.3644, 0.0987), (0.2357, 0.6656, 0.0987), (0.2660, 0.5001, 0.2339), (0.3202, 0.5128, 0.1670), (0.1708, 0.7593, 0.0699), (0.0787, 0.7882, 0.1331), (0.7369, 0.1784, 0.0847)},

$\mathrm{N}^-$ = {(0.7312, 0.2130, 0.0558), (0.1942, 0.7250, 0.0808), (0.4803, 0.3220, 0.1978) (0.3334, 0.5335, 0.1331), (0.2986, 0.4781, 0.2233), (0.3587, 0.5259, 0.1155) (0.1860, 0.7204, 0.0936), (0.1508, 0.7870, 0.0622), (0.7157, 0.2015, 0.0829)}.

The results of the IF-TOPSIS model are presented in Table 12.

**Table 12:** Results of the IF-TOPSIS method

| Alternative | $J_\gamma\left(H_i, \mathrm{N}^+\right)$ | $J_\gamma\left(H_i, \mathrm{N}^-\right)$ | $CC_i$ | Ranking Order |
|---|---|---|---|---|
| $H_1$ | 0.0028 | 0.0031 | 0.5254 | 2 |
| $H_2$ | 0.0027 | 0.0040 | 0.5970 | 1 |
| $H_3$ | 0.0044 | 0.0032 | 0.4211 | 3 |

The prioritization of treatment choices is $H_2 \succ H_1 \succ H_3$ and the alternative $H_2$ has the higher degree of suitability for treatment choice than others.

### 6.3. IF-VIKOR model

The IF-VIKOR model(Luo and Wang, 2017)consists of the following steps:

**Steps 1-5:** Same as the presented method.

**Step 6:** Derive the “group utility (GU)” and “individual regret (IR)” of each option.

The key focus of the original VIKOR technique is to effectively rank and determine the compromise solution for a given problem that has some contradictory criteria. For the compromise solution, multiple measures are presented from the $L_p$ – metric that is applied as an aggregated value to a compromise solution model as follows:

$$L_{p,\,i} = \left( \sum_{j=1}^{n} \left( \varphi_j \frac{J_\gamma\left(\mathrm{N}_j^+, y_{ij}\right)}{J_\gamma\left(\mathrm{N}_j^+, \mathrm{N}_j^-\right)} \right)^p \right)^{1/p},\ \gamma = 1,\ 2, \tag{27}$$

wherein $\varphi_j$ is the weight of $P_j$ $(j = 1, 2, \cdots, n)$.

With the divergence value-based $L_p$-metric, the GU and IR are presented by Eqs (28) and (29).

$$\mathbb{G}_i = L_{1,\,i} = \sum_{j=1}^{n} \left( \varphi_j \frac{J_\gamma\left(\mathrm{N}_j^+, y_{ij}\right)}{J_\gamma\left(\mathrm{N}_j^+, \mathrm{N}_j^-\right)} \right), \tag{28}$$

$$\mathfrak{R}_i = L_{\infty,\,i} = \max_{1 \le j \le n} \left( \varphi_j \frac{J_\gamma\left(\mathrm{N}_j^+, y_{ij}\right)}{J_\gamma\left(\mathrm{N}_j^+, \mathrm{N}_j^-\right)} \right). \tag{29}$$

**Step 7:** Compute of the "compromise solution (CS)" of each option.

The VIKOR technique's stimulus is to find the CS that is amidst an extreme GU for the least and majority of the IR for opponents. This study defines the CS $\vartheta_i$, $\forall\, i$ as

$$\vartheta_i = \lambda \frac{\mathbb{G}_i - \mathbb{G}^+}{\mathbb{G}^- - \mathbb{G}^+} + (1-\lambda) \frac{\mathfrak{R}_i - \mathfrak{R}^+}{\mathfrak{R}^- - \mathfrak{R}^+}, \tag{30}$$

where $\mathbb{G}^+ = \min_i \mathbb{G}_i$, $\mathbb{G}^- = \max_i \mathbb{G}_i$, $\mathfrak{R}^+ = \min_i \mathfrak{R}_i$, $\mathfrak{R}^- = \max_i \mathfrak{R}_i$ and $\lambda$ is the weight or decision mechanism coefficient. With no generality loss, we take the value as 0.5. The smaller the value of $\vartheta_i$ $(i = 1, 2, \cdots, m)$, the better the option $H_i$ $(i = 1, 2, \cdots, m)$. The compromise solution can be chosen with "voting by majority $(\lambda > 0.5)$" with "consensus $(\lambda = 0.5)$" and with "veto $(\lambda < 0.5)$".

**Step 8:** Rank the alternative.

The VIKOR approach involves ranking the alternative(s) $H_i$, $\forall\, i$ which corresponds to the values of $\mathbb{G}_i$, $\mathfrak{R}_i$ and $\vartheta_i$. The obtained result contains three ranking lists signified as $\mathbb{G}_i$, $\mathfrak{R}_i$ and $\vartheta_i$. We suggest the most appropriate one (the smallest among $\vartheta_i$ values) as a CS with handling the given necessary conditions given in Luo and Wang (2017). Here, the results of the IF-VIKOR technique are illustrated in Table 13.

**Table 13:** Outcomes of $\mathbb{G}_i$, $\Re_i$ and $\vartheta(\tau)$ and the CS of each option

| | $H_1$ | $H_2$ | $H_3$ | Ranking | Compromise Solution |
|---|---|---|---|---|---|
| $\mathbb{G}$ | 0.5875 | 0.2604 | 0.6369 | $H_2 \succ H_1 \succ H_3$ | $H_2$ |
| $\Re$ | 0.1269 | 0.1070 | 0.1719 | $H_2 \succ H_1 \succ H_3$ | $H_2$ |
| $\vartheta(\tau)$ | 0.3066 (0.0)<br>0.4191(0.2)<br>0.5877 (0.5)<br>0.7564 (0.8)<br>0.8688 (1.0) | 0.0000 (0.0)<br>0.0000 (0.2)<br>0.0000 (0.5)<br>0.0000 (0.8)<br>0.0000 (1.0) | 1.0000 (0.0)<br>1.0000 (0.2)<br>1.0000 (0.5)<br>1.0000 (0.8)<br>1.0000 (1.0) | $H_2 \succ H_1 \succ H_3$ | $H_2$ |

The prioritization of treatment option is $H_2 \succ H_1 \succ H_3$ and the alternative $H_2$ has the higher degree of suitability for treatment choice.

Additionally, we elucidate a systematic comparison of the present IF-CoCoSo with other MCDM approaches according to the several important standards applied in decision-making procedure (see Table 14). It can be concluded from Table 14 that the presented model is absolutely a novel contribution as it incorporates all major aspects of MCDM methods by comparing with the extant studies on MCDM approaches within IFSs settings.

**Table 14:** A comparative discussion of the ranking orders with various methods

| Tools | Standards | Criteria weights | MCDM Model | Assessing HD | Expert weights | Ranking order | Optimal choice |
|---|---|---|---|---|---|---|---|
| IVF-ELECTRE (Vahdani and Hadipour, 2011) | Interval-valued fuzzy ELECTRE method | Assumed | Outranking model | Excluded | Not considered | $H_2 \succ H_1$<br>$H_3 \succ H_1$ | $H_2$, $H_3$ |
| IF-TOPSIS (Joshi and Kumar, 2014) | Distance measure based TOPSIS method | Entropy measure method | Compromising model | Excluded | Not considered | $H_2 \succ H_1 \succ H_3$ | $H_2$ |
| IF-VIKOR (Luo and Wang, 2017) | Novel distance measure-based VIKOR method | Entropy measure method | Compromising model | Included | Considered (Entropy measure method) | $H_2 \succ H_1 \succ H_3$ | $H_2$ |
| IF-WASPAS method | Similarity measure- | Similarity | Scoring model | Included | Not considered | $H_2 \succ H_1 \succ H_3$ | $H_2$ |

| Tools | Standards | Criteria weights | MCDM Model | Assessing HD | Expert weights | Ranking order | Optimal choice |
|---|---|---|---|---|---|---|---|
| Mishra et al. (2019a) | based WASPAS | measure method | (utility based method) | | | | |
| Proposed IF-CoCoSo method | Proposed divergence measure and GSF-based CoCoSo method | Proposed divergence measure and GSF | Compromising model | Included | Considered (Score function model) | $H_2 \succ H_1 \succ H_3$ | $H_2$ |

## 7. Conclusions

To characterize uncertainty and fuzziness arguments in evaluating the medical decision-making problem, IFSs were implemented and evaluative criteria were recognized, which contain various qualitative and quantitative influencing parameters from the physician to medical field. The present study has significant contributions to current knowledge on the decision-making methodology. First, an innovative GSF was proposed to mark out the most appropriate alternatives from the possible alternatives where the decision matrix, which is related to various criteria in regard to choosing the attributes, is characterized in IFSs. In addition, it was examined from the developed score function that the enhanced score function introduced by Liu & Wang (2007) is obtained as a special case by taking $(\gamma_1, \gamma_2) = \left(\frac{1}{2}, \frac{1}{2}\right)$ and thus, the GSF is of a higher profitability for obtaining the expert goals during their implementation in comparison with those that are currently used. Second, two new parametric IF-divergence measures of order α and (α,β) were developed through taking into consideration the MF, NF and HF and various attractive properties of the proposed measures that have been studied. Third, a new compromising method, i.e., the extended CoCoSo method, was presented to handle medical MCDM problems with IFSs with the proposed parametric divergence measure and GSF. We developed a method to evaluate criteria weights with IFNs. Finally, we implemented the IF-CoCoSo method to rank and evaluate the therapies for medical MCDM problem. The effectiveness of the developed approach is justified by some comparative analyses.

In the future, researchers can be extended the CoCoSo method in different uncertain environments such as “hesitant fuzzy sets (HFSs)”, PFSs, FFSs, “interval-valued Fermatean fuzzy sets (IVFFSs)”. In addition, we will continue this study with expectation that the model could be considered more appropriate to other decision-making issues such as selection of disinfection facility for healthcare waste, low carbon suppliers assessment, blockchain technology adoption and so many others.

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