FACTA UNIVERSITATIS
Series: **Mechanical Engineering**
https://doi.org/10.22190/FUME241001052M

Original scientific paper

INTUITIONISTIC FUZZY MACONT METHOD FOR LOGISTICS 4.0 BASED CIRCULAR ECONOMY INTERESTED REGIONS ASSESSMENT IN THE AGRI-FOOD SECTOR

Arunodaya Raj Mishra[1], Pratibha Rani[2], Dragan Pamucar[3], Ahmad M. Alshamrani[4], Adel Fahad Alrasheedi[4]

[1]Department of Mathematics, Government College Raigaon, Madhya Pradesh, India
[2]Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai, Tamil Nadu, India
[3]Department of Operations Research and Statistics, Faculty of Organizational Sciences, University of Belgrade, Belgrade, Serbia
[4]Department of Statistics and Operations Research, College of Science, King Saud University, Riyadh, Saudi Arabia

Abstract. *This study aims to evaluate and prioritize the key interested regions of Circular Economy (CE) in terms of implementing the industry 4.0 technologies for the performance of logistics activities in the agri-food sector. For this purpose, we introduce a hybrid ranking framework based on Relative Closeness Coefficient (RCC)-based objective weighting model, the RANking COMparison (RANCOM) subjective weighting procedure and the Mixed Aggregation by Comprehensive Normalization Technique (MACONT) with Intuitionistic Fuzzy Information (IFI). In this framework, new IF-score function and an improved distance measure are proposed in the context of IFI to evade the limitations of existing ones. A hybrid IF-RCC-RANCOM-MACONT framework is introduced to prioritize the options over defined criteria. To prove the applicability of introduced approach, it is employed on a case study of circular economy interested regions assessment in the agri-food sector, consisting of five alternatives and nine criteria under the dimensions of sustainability. Sensitivity analysis is shown to highlight the impact of used parameters on the final outcomes. At last, a comparison with extant approaches is made to demonstrate the robustness of obtained results.*

Key words: *Logistics 4.0, Circular economy, Agri-food sector, Intuitionistic fuzzy sets, Distance measure, Score function, MACONT, Multi-criteria decision-making*

Received: October 01, 2024 / Accepted December 30, 2024
Corresponding author: Pratibha Rani
Saveetha School of Engineering, Saveetha Institute of Medical and Technical Sciences (SIMATS), Chennai-602105, Tamil Nadu, India
E-mail: pratibha138@gmail.com

© 2024 by University of Niš, Serbia | Creative Commons License: CC BY-NC-ND

1. INTRODUCTION

Logistics management is the governance of supply chain management (SCM) functions that integrates the activities such as planning, packaging, material handling, warehousing, management of forward and reverse flow of goods, transportation, services and associated information between the point of origin and point of consumption to meet customers' supplies [1-3]. "Forward logistics (FL)" consisting of a procedure of moving goods from the point of production to end customer. As a counter-part of FL, "reverse Logistics (RL)" refers to the procedure which reverses common flow of raw materials or finished goods along supply chain (SC) [4-8]. The purpose of efficient logistics management is to ensure customer satisfaction, achieve maximum competitiveness and profitability for the business along with the well-planned network of SC, including the end consumer [9, 10]. Both the logistics processes are covered by the term "closed-loop supply chain (CLSC)", where goods lifecycle management is incorporated with its logistics solutions [11, 12].

In the past decade, the need for a transition towards a circular economy (CE) has been studied by several user groups and industries. The CE concept is defined as an economic system that aims to minimize the environmental and material footprint together with industrial transformation at different levels [13]. Moving towards a CE system offers a chance to bring business profits including advanced competitiveness, resource security, flexible and diverse business models to enable value formation [14, 15]. In the current age of growing resource scarcity, different researchers, policymakers, and business managers have made empirical assessments on the impact of adopting the CE principle, which does not only cover the reverse flow but also manage the forward flow of the SC involving operations of newer materials [16].

As a revolutionary digitalization, logistics 4.0 refers to the implementation of different digital technologies into logistics operations to optimize and streamline the SCM [17-19]. The paradigms of CE and logistics 4.0 offers several opportunities to create more sustainable and effective SC procedure. Food insecurity can lead to significant productivity losses, lesser cognitive facility and reduced work performance. Although, the agri-food sector cannot allow itself to missed the possibilities initiated by the convergence of logistics 4.0 and the CE. In this work, we consider the potentials of employing industry 4.0 (I4.0) for executing the logistics processes in the CE interest regions under the context of agri-food sector. This selection process may also include several DEs, whose opinions may differ and ambiguous. Considering the hesitation levels, knowledge and expertise of DEs, fuzzy set theory (FST) and its generalizations are preferred to handle the incomplete and imprecise information of such type of problems [20-23].

As one of the extensions of FST, the notion of intuitionistic fuzzy set (IFS) [24] has received much attention to deal with ambiguous and vague data. In IFSs, every object is described by the membership grade (MG) and non-membership grade (NG) with their sum is restricted to one. Çelik et al. [25] ensured socio-economic sustainability indicators of medical waste management (MWM). In this regard, they presented a unified approach with the weighting and ranking models and applied for MWM in six hospitals, where the data is given in terms of intuitionistic fuzzy numbers. Asif et al. [26] gave various form Hamacher operators to deal with different decision-making problems. Bajaj & Kumar [27] studied a new correlation measure on IFSs and implemented to the pattern recognition, medical diagnosis and clustering problems. Further, an integrated decision support tool has been presented to evaluate the alternatives on IFSs. Majumder et al. [28] gave an IF-multiple criteria decision-making (MCDM) approach for deriving the significance values of criteria. Moreover, they used a unique decision support system to assume a feasibility assessment of solar power plant. Wan et al. [29] integrated IF-best worst method (BWM) with additive consistency. Based on this method, they gave a non-linear programming procedure for solving MCDM problems. Hussain and Ullah [30] presented a model using Sugeno-Weber aggregation operators on to solve real-life MCDM problem. Şahin et al. [31] used two methods, geographic information measure and IFSs-based method to evaluate and rank the locations for solar-wind power plant establishment in Netherlands.

Considering the multiple criteria/factors and decision experts (DEs), choosing and prioritizing an appropriate CE interested regions in agri-food sector can be defined as a multiple criteria group decision-making (MCGDM) problem [32, 33]. To handle the MCDM problems, Wen et al. [34] initiated novel idea of Mixed Aggregation by COmprehensive Normalization Technique (MACONT) approach to execute and make three normalized assessment degrees into a single normalized degree to estimate the deviations of original data. The process of classical MACONT approach includes (i) different normalization techniques for finding the normalized performance values of options with respect to considered evaluation criteria; (ii) aggregating three normalized performance values; (iii) determining the virtual reference option; (iv) using two arithmetic and geometric operators to determine distances between each option and reference option and finding the subordinate comprehensive scores of options; (v) deriving final comprehensive degrees of options and accordingly prioritize the options. Truong & Li [35] proposed an integrated MACONT approach based on the Dempster-Shafer doctrine and e-STEP procedure for multiple attribute tradeoff assessment in transportation budget sharing. With the integration of different strategies, Nguyen et al. [36] developed an improved MACONT method and compared with existing normalization-based techniques. Apart from these studies, several other applications of MACONT method have been established in the literature [37-39]. Further, RANking COMparison (RANCOM) is a pairwise comparison structure using a three-value measure [40]. The RANCOM is considered for less experienced DEs, is categorized by strength to conflicts in criterion associations, is intuitive, time-efficient for dealing complex MCGDM problems, and handles with imprecisions in evaluations of DEs while certifying high repeatability of outcomes. The RANCOM comprises finding criterion preferences, constructing a matrix of ranking comparison (MAC) with pairwise assessments, computing summed criteria weights (SCW), and estimating overall weights of different criteria. As per authors' knowledge, there is no work which introduces IF-modified RCC-RANCOM-MACONT method integrating an IF-score function-based DEs' weighting procedure, the IF-modified relative closeness coefficient (RCC)-based objective weighting model, the IF-RANCOM subjective weighting procedure and the MACONT framework on IFI. The main contributions and novelties of the work are given as

- New IF-score function is developed to evade the drawbacks of existent IF-score functions (Xu [41] Xu et al. [42], Zeng et al. [43], Feng et al. [44]).
- New IF-distance measure is introduced to conquer the advantages of prior developed IF-distances (Shen et al. [45], Tripathi et al. [46], Wu et al. [47], Ejegwa & Agbetayo [48], Li et al. [49]).
- A hybrid ranking approach is proposed by integrating the IF-score function-based experts' weighting model, an objective-subjective criteria weight-determining model and the MACONT method with IFI

- To exemplify the feasibility and efficacy of introduced ranking framework, it is implemented to a case study of prioritizing the CE interested regions areas in agri-food sector.

Rest part of this paper is organized in the following way. Section 2 confers the background of the work. Section 3 first develops new IF-score function and its effectiveness over the existent IF-score functions. Further, this section proposes a distance measure for IFSs and discusses its properties. Comparative study is performed to verify the consistency and rationality of introduced measure. Section 4 introduces a hybrid multi-criteria evaluation method, namely IF-modified RCC-RANCOM-MACONT. Section 5 implements the proposed method for prioritizing CE interested regions in the agri-food sector. Moreover, this section conducts sensitivity and comparative investigations to validate the determined outcomes. Finally, Section 6 confers the conclusions of the paper.

2. New Score Function and Distance Measure for IFSs

This part of the study first presents the concepts of IFSs. To show comparison diverse IFNs, new IF-score function is introduced to reveal the effectiveness over the existing IF-score functions. Next, a modified IF-distance measure is introduced to describe dissimilarity on IFSs and further compared with previously introduced measures.

2.1 Preliminaries

Here, we present the fundamental definitions used in this work.

Definition 2.1 [24]. Let $V = \{v_1, v_2, \ldots, v_t\}$ be the fixed universe of discourse. In 1986, Atanassov [24] presented the mathematical definition of IFS B on $V = \{v_1, v_2, \ldots, v_t\}$, given by Eq. (1) as

$$B=\left\{\left(v_l,\left(\mu_B(v_l),\nu_B(v_l)\right)\right)\middle| v_l\in V\right\}, \tag{1}$$

where μ_B: $V \to [0, 1]$ and ν_B: $V \to [0, 1]$ symbolize MG and NG of a member $v_l \in V$ to B, respectively, satisfying $0 \le \mu_B(v_l) + \nu_B(v_l) \le 1$. The hesitancy degree is defined as $\pi_B(v_l)= 1- \mu_B(v_l) - \nu_B(v_l)$, for each $v_l \in V$. The term "$(\mu_B(v_l), \nu_B(v_l))$" is termed as intuitionistic fuzzy number (IFN) and indicated in this study as $\psi = (\mu, \nu)$, where $\mu, \nu \in [0, 1]$ and $0 \le \mu + \nu \le 1$.

Definition 2.2 [41]. For any two IFNs $\psi_1 = (\mu_1, \nu_1)$ and $\psi_2 = (\mu_2, \nu_2)$, some basic operations are discussed as

a) $\psi_1^c = (\nu_1, \mu_1)$,

b) $\psi_1 \cap \psi_2 = \left((\mu_1 \wedge \mu_2), (\nu_1 \vee \nu_2)\right)$,

c) $\psi_1 \cup \psi_2 = \left((\mu_1 \vee \mu_2), (\nu_1 \wedge \nu_2)\right)$,

d) $\psi_1 \oplus \psi_2 = \left(\mu_1 + \mu_2 - \mu_1\mu_2, \nu_1\nu_2\right)$,

e) $\psi_1 \otimes \psi_2 = \left(\mu_1\mu_2, \nu_1 + \nu_2 - \nu_1\nu_2\right)$,

f) $\zeta\psi_1 = \left(1-(1-\mu_1)^\zeta, (\nu_1)^\zeta\right), \zeta > 0$,

g) $\psi_1^\zeta = \left((\mu_1)^\zeta, 1-(1-\nu_1)^\zeta\right), \zeta > 0$.

Definition 2.3 [41]. For an IFN $\psi = (\mu, \nu)$, IF-score function and IF-accuracy function are defined via Eq. (2) and Eq. (3), respectively.

$$S_X(\psi) = (\mu - \nu), \text{ where } S_X(\psi) \in [-1,1],$$

$$A(\psi) = \mu + \nu, \text{ where } A(\psi) \in [0,1].$$

Xu et al. [42] gave the normalized version of IF-score function and defined as follows:

$$S_{XW}(\psi) = \frac{1}{2}(1 + \mu - \nu), \text{ where } S_{XW}(\psi) \in [0,1].$$

Further, Feng et al. [44] presented the generalized version of IF-score function and defined as follows: For $p > 1$,

$$S_{FZ}(\psi) = \left(\frac{\mu^p + (1-\nu)^p}{2}\right)^{1/p}, \text{ where } S_{FZ}(\psi) \in [0,1].$$

In recent times, Zeng et al. [43] developed the logarithmic function-based IF-score function and defined as follows:

$$S_{ZC}(\psi) = \mu - \nu - (1 - \mu - \nu) \times \frac{\log_2(2 - \mu - \nu)}{100}, \text{ where } S_{ZC}(\psi) \in [0,1].$$

Definition 2.4 [41]. To aggregate the IFNs, Xu [41] introduced an "IF-weighted average (IFWA)" operator and an "IF-weighted geometric (IFWG)" operator on IFNs $\psi_l = (\mu_l, \nu_l)$, $l = 1, 2, \ldots, t$, and given as

$$IFWA(\psi_1, \psi_2, \ldots, \psi_t) = \left(1 - \prod_{l=1}^{t}(1-\mu_l)^{w_l}, \prod_{l=1}^{t}(\nu_l)^{w_l}\right), \tag{2}$$

$$IFWG(\psi_1, \psi_2, \ldots, \psi_t) = \left(\prod_{l=1}^{t}(\mu_l)^{w_l}, 1 - \prod_{l=1}^{t}(1-\nu_l)^{w_l}\right), \tag{3}$$

where, the set $\{w_1, w_2, \ldots, w_t\}$ denotes the weights of IFNs $\psi_l = (\mu_l, \nu_l)$, $l = 1, 2, \ldots, t$, and w_l lies between 0 and 1, and $w_1+w_2+\ldots+w_t = 1$.

Definition 2.5 [50]. Let $A, B, H \in IFSs(V)$. A real-valued function d: $IFSs(V) \times IFSs(V) \rightarrow [0,1]$ is said to be a distance measure for IFSs if it holds the following requirements:

(i). $0 \le d(A, B) \le 1$,

(ii). $d(A, B)$ if and only if $A = B$,

(iii). $d(A, B) = d(B, A)$,

(iv). If $A \subseteq B \subseteq H$, then $d(A, B) \le d(A, H)$ and $d(B, H) \le d(A, H)$.

2.2. New Score Function for IFN

To rank the IFNs, Xu [41] defined the concept of score and accuracy functions. Further, many improved score functions have been introduced in the context of IFNs, while some of the well-known IF-score functions, presented in Definition 2.3 (Xu [41], Xu et al. [42], Zeng et al. [43], Feng et al. [44]) present unreasonable results during the comparison of different pairs of IFNs. To this aim, this paper proposes a new score function for an IFN.

For an IFN $\psi = (\mu, \nu)$, we present a new IF-score function, defined as

$$S(\psi)=\frac{1}{2(e+1)}\left(\sqrt{\mu}\,e^{\left(\sqrt{\mu}\right)}+\sqrt{1-\nu}\,e^{\left(\sqrt{1-\nu}\right)}+\left(\sqrt{\mu}+\sqrt{1-\nu}\right)\sqrt{\frac{1+\mu-\nu}{2}}\right). \tag{4}$$

Using Eq. (4), we discuss the given axioms:

Property 2.1. The IF-score function $S(\psi)$ given in Eq. (4), increases monotonically w. r. t. μ and decreases monotonically w. r. t. ν.

Property 2.2. The developed IF-score function fulfils $S((0, 1)) = 0$ and $S((1, 0)) = 1$.

Property 2.3. Let $\psi_1 = (\mu_1, \nu_1)$ and $\psi_2 = (\mu_2, \nu_2)$ be the IFNs. If $\mu_1 > \mu_2$ and $\nu_1 < \nu_2$, then $S(\psi_1) > S(\psi_2)$.

The following example shows the drawbacks of existent IF-score functions

Example 2.1. Let us suppose a pair of IFNs, given as $\psi_1 = (0.5, 0.5)$ and $\psi_2 = (0.3, 0.3)$. To compare these IFNs, we apply the proposed and existing IF-score functions and obtain the results as follows. It is clear that existent IF-score functions by Xu [41], Xu et al. [42] and Feng et al. [44] are unable to discriminate these two different IFNs as $S_X(\psi_1) = 0 = S_X(\psi_2)$, $S_{XW}(\psi_1) = 0.5 = S_{XW}(\psi_2)$ and $S_{FZ}(\psi_1) = 0.5 = S_{FZ}(\psi_2)$ ($p = 1$), while the proposed score function (4) obtains the result as $S(\psi_1) = 0.341$ and $S(\psi_2) = 0.318$. Thus, $\psi_1 > \psi_2$.

Example 2.2. Consider that $\psi_1 = (0.7, 0.3)$ and $\psi_2 = (0.6, 0.2)$ are two IFNs. The score functions by Xu [41], Xu et al. [42], Zeng et al. [43] and Feng et al. [44] are unable to make difference between given IFNs as $S_X(\psi_1) = 0.4 = S_X(\psi_2)$, $S_{XW}(\psi_1) = 0.7 = S_{XW}(\psi_2)$, $S_{ZC}(\psi_1) = 0.4 = S_{ZC}(\psi_2)$ $S_{ZC}\left(\psi_1\right)=0.4=S_{ZC}\left(\psi_2\right)$ and $S_{FZ}(\psi_1) = 0.7 = S_{FZ}(\psi_2)$ ($p > 1$), while the proposed IF-score function gives a reasonable result, which as $S(\psi_1) = 0.484$ and $S(\psi_2) = 0.505$. Thus, $\psi_1 < \psi_2$. It demonstrates the usefulness of developed IF-score function over several extant functions [41-44].

2.3. New Distance Measure for IFSs

To quantify the dissimilarity between IFSs, the concept of distance measure has been proposed by Szmidt & Kacprzyk [51]. In the past decade, several IF-distance measures have been introduced with wider perspectives, while some of them (Shen et al. [45], Tripathi et al. [46], Wu et al. [47], Ejegwa & Agbetayo [48], Li et al. [49]) present counter-intuitive results in the measurement of dissimilarity between IFSs.

For E, $G \in IFSs(V)$, we develop a modified distance measure for describing the dissimilarity between IFSs A and B:

$$d(A,B)=\frac{1}{7t}\sum_{l=1}^{t}\left[\begin{array}{l}\left|\mu_A(v_l)-\mu_B(v_l)\right|+\left|\nu_A(v_l)-\nu_B(v_l)\right|+\left|\pi_A(v_l)-\pi_B(v_l)\right|+\left|\mu_A(v_l)\nu_B(v_l)-\mu_B(v_l)\nu_A(v_l)\right| \\ +\left|\mu_A(v_l)\pi_B(v_l)-\mu_B(v_l)\pi_A(v_l)\right|+\left|\nu_A(v_l)\pi_B(v_l)-\nu_B(v_l)\pi_A(v_l)\right| \\ +\Big(\left|\min\{\mu_A(v_l),\, \nu_B(v_l)\}-\min\{\mu_B(v_l),\, \nu_A(v_l)\}\right|+\left|\max\{\mu_A(v_l),\, \nu_B(v_l)\}\right. \\ \left.-\max\{\mu_B(v_l),\, \nu_A(v_l)\}\right|\Big)+\Big(\left|\min\{\mu_A(v_l),\, \pi_B(v_l)\}-\min\{\mu_B(v_l),\, \pi_A(v_l)\}\right| \\ +\left|\max\{\mu_A(v_l),\, \pi_B(v_l)\}-\max\{\mu_B(v_l),\, \pi_A(v_l)\}\right|\Big)+\Big(\left|\min\{\nu_A(v_l),\, \pi_B(v_l)\}\right. \\ \left.-\min\{\nu_B(v_l),\, \pi_A(v_l)\}\right|+\left|\max\{\nu_A(v_l),\, \pi_B(v_l)\}-\max\{\nu_B(v_l),\, \pi_A(v_l)\}\right|\Big)\end{array}\right]. \tag{5}$$

Theorem 2.1. The function d (A, B), presented by Eq. (5), is a valid distance measure for IFSs.

Proof. To prove this theorem, we need to verify the properties (i)-(iv) of Definition 2.5.

(i). For any two IFSs A and B, we know that $0 \leq \mu_A(v_l), \mu_B(v_l) \leq 1$, $0 \leq \nu_A(v_l), \nu_B(v_l) \leq 1$ and $0 \leq \pi_A(v_l), \pi_B(v_l) \leq 1$, for each $v_l \in V$. It implies that each term of Eq. (5) ranges between 0 and 1 and thus, $0 \leq d(A, B) \leq 1$.

(ii). Consider that $d(A, B) = 0$. As each term of Eq. (5) lies between 0 and 1, therefore, from our assumption, $d(A, B) = 0$ is only possible when every term of Eq. (5) should be equal to zero. It implies that $\mu_A(v_l) = \mu_B(v_l)$, $\nu_A(v_l) = \nu_B(v_l)$ and $\pi_A(v_l) = \pi_B(v_l)$, for each $v_l \in V$. Hence, $A = B$. Conversely, if $A = B$, then it is obvious from Eq. (5) that $d(A, B) = 0$. Hence, $d(A, B) = 0$ iff $A = B$.

(iii). It is clear from the property of modulus and IFS, so we have omitted the proof.

(iv). For any three IFSs A, B and H on a finite universe of discourse $V = \{v_1, v_2, \ldots, v_t\}$, if $A \subseteq B \subseteq H$, then $0 \leq \mu_A(v_l) \leq \mu_B(v_l) \leq \mu_H(v_l) \leq 1$, $0 \leq \nu_H(v_l) \leq \nu_B(v_l) \leq \nu_A(v_l) \leq 1$ and $0 \leq \pi_H(v_l) \leq \pi_B(v_l) \leq \pi_A(v_l) \leq 1$. It implies that for each $v_l \in V$, we have

$$|\mu_A(v_l) - \mu_B(v_l)| \leq |\mu_A(v_l) - \mu_H(v_l)|,\ |\nu_A(v_l) - \nu_B(v_l)| \leq |\nu_A(v_l) - \nu_H(v_l)|,$$
$$|\pi_A(v_l) - \pi_B(v_l)| \leq |\pi_A(v_l) - \pi_H(v_l)|,$$
$$0 \leq \min\{\mu_A(v_l),\ \nu_H(v_l)\} \leq \min\{\mu_A(v_l),\ \nu_B(v_l)\} \leq \min\{\mu_B(v_l),$$
$$\leq \nu_A(v_l)\} \leq \min\{\mu_H(v_l), \nu_A(v_l)\} \leq 1,$$
$$0 \leq \min\{\mu_A(v_l),\ \pi_H(v_l)\} \leq \min\{\mu_A(v_l),\ \pi_B(v_l)\} \leq \min\{\mu_B(v_l), \pi_A(v_l)\} \leq \min\{\mu_H(v_l), \pi_A(v_l)\} \leq 1,$$
$$0 \leq \min\{\nu_A(v_l), \pi_H(v_l)\} \leq \min\{\nu_A(v_l), \pi_B(v_l)\} \leq \min\{\nu_B(v_l), \pi_A(v_l)\} \leq \min\{\nu_H(v_l), \pi_A(v_l)\} \leq 1,$$
$$0 \leq \max\{\mu_A(v_l),\ \nu_H(v_l)\} \leq \max\{\mu_A(v_l),\ \nu_B(v_l)\} \leq \max\{\mu_B(v_l),\ \nu_A(v_l)\} \leq \max\{\mu_H(v_l),\ \nu_A(v_l)\} \leq 1,$$
$$0 \leq \max\{\mu_A(v_l),\ \pi_H(v_l)\} \leq \max\{\mu_A(v_l),\ \pi_B(v_l)\} \leq \max\{\mu_B(v_l),\ \pi_A(v_l)\} \leq \max\{\mu_H(v_l), \pi_A(v_l)\} \leq 1,$$
$$0 \leq \max\{\nu_A(v_l), \pi_H(v_l)\} \leq \max\{\nu_A(v_l), \pi_B(v_l)\} \leq \max\{\nu_B(v_l), \pi_A(v_l)\} \leq \max\{\nu_H(v_l), \pi_A(v_l)\} \leq 1,$$

Also,

$$|\mu_A(v_l)\nu_H(v_l) - \mu_H(v_l)\nu_A(v_l)| \geq |\mu_A(v_l)\nu_B(v_l) - \mu_B(v_l)\nu_A(v_l)|,$$
$$|\mu_A(v_l)\pi_H(v_l) - \mu_H(v_l)\pi_A(v_l)| \geq |\mu_A(v_l)\pi_B(v_l) - \mu_B(v_l)\pi_A(v_l)|,$$
$$|\nu_A(v_l)\pi_H(v_l) - \nu_H(v_l)\pi_A(v_l)| \geq |\nu_A(v_l)\pi_B(v_l) - \nu_B(v_l)\pi_A(v_l)|, \forall v_l \in V.$$

Hence, it shows that $d(A, B) \leq d(A, H)$. Similarly, we can prove that $d(B, H) \leq d(A, H)$.

Example 2.3. Let us assume some pairs of IFSs, which are *Case-1: {A= (0.7, 0.3), B = (0, 0)}*, *Case-2: {A = (0.4, 0.6), B = (0, 0)}*, *Case-3: {A = (0.5, 0.45), B = (0.55, 0.4)}*, *Case-4: {A = (0.45, 0.4), B = (0.45, 0.32)}*, *Case-5: {A = (0.3, 0.41), B = (0.5, 0.344)}* and *Case-6: {A = (0.41, 0.2), B = (0.22,0.28)}*. To compare each pair of IFSs, the proposed and existent IF-distance measures are applied to the given six pairs of IFSs. Table 1 presents the required computational results. From Table 1, we can observe the unreasonable results of existent measures, while the proposed IF-distance measure successfully obtains the discrimination between all the given pairs of IFSs.

Table 1 Comparative results of developed and extant IF-distance measures (Highlighted texts denote counter-intuitive results)

Measures	Case-1 $\{(v_1,0.7, 0.3)\}$ $\{(v_1,0,0)\}$	Case-2 $\{(v_1,0.4, 0.6)\}$ $\{(v_1,0,0)\}$	Case-3 $\{(v_1,0.5, 0.45)\}$ $\{(v_1,0.55, 0.4)\}$	Case-4 $\{(v_1,0.45, 0.4)\}$ $\{(v_1,0.45, 0.32)\}$	Case-5 $\{(v_1,0.3, 0.41)\}$ $\{(v_1,0.5, 0.344)\}$	Case-6 $\{(v_1,0.41,0.2)\}$ $\{(v_1, 0.22, 0.28)\}$
Shen et al. [45]	0.533	-0.033	0.05	0.026	0.152	0.155
Shen et al. [45]	0.539	0.51	0.052	0.052	0.159	0.192
Tripathi et al. [46]	0.582	0.684	0.001	0.005	0.013	0.013
Wu et al. [47]	0.351	0.306	0.05	0.046	0.139	0.139
Ejegwa & Agbetayo [48]	1.0	1.0	0.001	0.006	0.024	0.021
Li et al. [49]	1.0	1.0	0.036	0.081	0.156	0.146
Proposed measure	0.9143	0.8857	0.0504	0.0851	0.2051	0.1913

3. An Integrated IF-Modified RCC-RANCOM-MACONT Method for MCGDM Problems

In this section, we propose an improved version of MACONT approach that incorporates the DEs' weight-determining procedure, the IFWA operator, and an integrated objective-subjective weighting model with IFI. This approach firstly computes the DEs' weights through a collective IF-score function and rank reciprocal model and further calculates an aggregated IF-decision matrix (A-IFDM). Next, the weights of criteria are computed with the combination of objective and subjective weights via IF-modified RCC and IF-RANCOM models, respectively. Finally, the stepwise procedure of MACONT approach is presented to solve the MCDM problems with IFI. Fig. 1 presents the pictorial representation of the proposed framework.

This method involves subsequent procedural steps:

Step 1: Construction of linguistic decision-matrix (LDM).

For an IFI-based MCGDM problem, let $F = \{F_1, F_2, ..., F_m\}$ be a defined set of options over considered criteria set $R = \{R_1, R_2, ..., R_n\}$. To make an optimal decision, a committee of 'p' DEs $B = \{B_1, B_2, ..., B_p\}$ is invited to provide their opinion regarding the assessment of each option over defined criteria. Let $X = (x_{ij}^{(k)})_{m\times n}$ be an LDM, where $x_{ij}^{(k)}$ denotes the linguistic performance value of an option F_j over a criterion R_j presented by k^{th} DE. Further, the LDM is converted into IF-decision matrix (IFDM) using Likert scale.

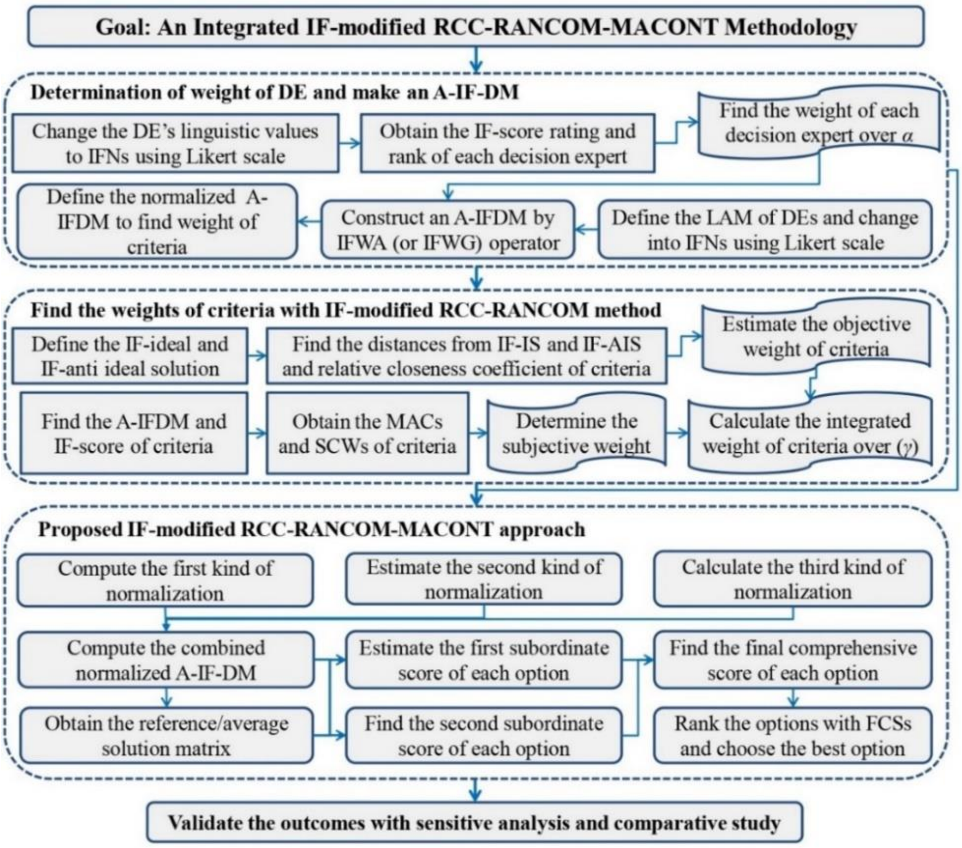

Fig. 1 Flow diagram of the IF-modified RCC-RANCOM-MACONT framework

Step 2: Computing the weights of DEs.

For determining the DEs' weights, let us consider a linguistic significance degree of each DE based on their skills, expertise and knowledge. Let $B_k = (\mu_k, \nu_k)$ be an IF-significance degree of k^{th} DE, then the weight of k^{th} DE is estimated as follows, where $k = 1, 2, 3, ..., p$.

Step 2.1: Using developed IF-score function, a normalized assessment rating of k^{th} DE is calculated, where $k = 1, 2, 3, ..., p$.

$$a_k = \frac{\left(\sqrt{\mu_k}\, e^{\left(\sqrt{\mu_k}\right)} + \sqrt{1-\nu_k}\, e^{\left(\sqrt{1-\nu_k}\right)} + \left(\sqrt{\mu_k} + \sqrt{1-\nu_k}\right)\sqrt{\frac{1+\mu_k-\nu_k}{2}}\right)}{\sum_{k=1}^{p}\left(\sqrt{\mu_k}\, e^{\left(\sqrt{\mu_k}\right)} + \sqrt{1-\nu_k}\, e^{\left(\sqrt{1-\nu_k}\right)} + \left(\sqrt{\mu_k} + \sqrt{1-\nu_k}\right)\sqrt{\frac{1+\mu_k-\nu_k}{2}}\right)}. \tag{6}$$

Step 2.2: Estimate the rank of each DE using proposed IF-score rating and estimate the rank (r_k) of each expert. Then, rank-based performance rating of each expert using the rank reciprocal weight of DE is estimated through Eq. (7) as

$$a_k^r = \frac{1/r_k}{\sum_{k=1}^{t} (1/r_k)}, \; k = 1, 2, ..., p. \tag{7}$$

Step 2.3: Based on the combination of Eq. (6) and Eq. (7) by means of a parameter 'α', we present the following formula to derive the overall weight of k^{th} DE, given by Eq. (8).

$$\lambda_k = \alpha(a_k) + (1-\alpha)(a_k^r), \; k = 1, 2, ..., \; p, \tag{8}$$

where $\alpha \in [0,1]$ denotes the expert weighting strategy coefficient for assigning significance degree to each DE. Moreover, λ_k denotes the weight vector of DEs' set $B = \{B_1, B_1, \ldots, B_p\}$ with λ_k belongs to [0,1] and $\lambda_1 + \lambda_2 + \ldots + \lambda_p = 1$.

Step 3: Determine the A-IFDM.

In this step, all individual opinions of DEs are collected through to obtain the combined performance degree of each option over defined criteria. To this aim, we use IFWA (or IFWG) operator to create an A-IFDM $\bar{X} = (\bar{x}_{ij})_{m\times n} = (\bar{\mu}_{ij}, \bar{\nu}_{ij}),$ where

$$\bar{x}_{ij} = (\bar{\mu}_{ij}, \bar{\nu}_{ij}) = \boldsymbol{IFWA}_{\lambda_k}\left(x_{ij}^{(1)}, x_{ij}^{(2)}, ..., x_{ij}^{(p)}\right) \text{ or } \boldsymbol{IFWG}_{\lambda_k}\left(x_{ij}^{(1)}, x_{ij}^{(2)}, ..., x_{ij}^{(p)}\right). \tag{9}$$

Step 4: Determination of criteria weights by IF-modified RCC-RANCOM model

During the procedure of MCDM, weight of criterion is an important aspect for the experts. In the present work, we propose new weighting model with the combination of objective weight using IF-modified RCC tool and subjective weight by IF-RANCOM tool with IFI. We discuss an integrated procedure based on the combination of IF-modified RCC and IF-RANCOM models.

Case I: Objective weighting through the IF-modified RCC model.

This approach involves subsequent steps:

Step 4a: Determine the positive distance matrix (PDM) $d(\bar{x}_{ij}, \rho^+)$ on an aggregated IFN $\bar{x}_{ij}$ and IF-positive ideal rating (IF-PIR) ρ^+ through Eq. (10).

$$d(\bar{x}_{ij}, \rho^+) = \frac{1}{7}\begin{bmatrix} \left|\bar{\mu}_{ij} - \mu_{\rho^+}\right| + \left|\bar{\nu}_{ij} - \nu_{\rho^+}\right| + \left|\bar{\pi}_{ij} - \pi_{\rho^+}\right| + \left|\bar{\mu}_{ij}\nu_{\phi^+} - \mu_{\phi^+}\bar{\nu}_{ij}\right| \\ + \left|\bar{\mu}_{ij}\,\pi_{\rho^+} - \mu_{\rho^+}\bar{\pi}_{ij}\right| + \left|\bar{\nu}_{ij}\pi_{\rho^+} - \nu_{\rho^+}\bar{\pi}_{ij}\right| \\ + \left(\left|\min\left\{\bar{\mu}_{ij}, \nu_{\rho^+}\right\} - \min\left\{\mu_{\rho^+}, \bar{\nu}_{ij}\right\}\right| + \left|\max\left\{\bar{\mu}_{ij}, \nu_{\rho^+}\right\} - \max\left\{\mu_{\rho^+}, \bar{\nu}_{ij}\right\}\right|\right) \\ + \left(\left|\min\left\{\bar{\mu}_{ij}, \pi_{\rho^+}\right\} - \min\left\{\mu_{\rho^+}, \bar{\pi}_{ij}\right\}\right| + \left|\max\left\{\bar{\mu}_{ij}, \pi_{\rho^+}\right\} - \max\left\{\mu_{\rho^+}, \bar{\pi}_{ij}\right\}\right|\right) \\ + \left(\left|\min\left\{\bar{\nu}_{ij}, \pi_{\rho^+}\right\} - \min\left\{\nu_{\rho^+}, \bar{\pi}_{ij}\right\}\right| + \left|\max\left\{\bar{\nu}_{ij}, \pi_{\rho^+}\right\} - \max\left\{\nu_{\rho^+}, \bar{\pi}_{ij}\right\}\right|\right) \end{bmatrix}, \tag{10}$$

where $\bar{x}_{ij} = (\bar{\mu}_{ij}, \bar{\nu}_{ij})$ and $\rho^+ = (\mu_{\rho^+}, \nu_{\rho^+}) = (1, 0)$.

Compute the negative distance matrix (NDM) $d(\bar{x}_{ij}, \rho^-)$ on an aggregated IFN $\bar{x}_{ij}$ and IF-negative ideal rating (IF-NIR) ρ^- via Eq. (11).

$$d\left(\bar{x}_{ij},\rho^{-}\right)=\frac{1}{7}\left[\begin{array}{l}\left|\bar{\mu}_{ij}-\mu_{\rho^{-}}\right|+\left|\bar{\nu}_{ij}-\nu_{\rho^{-}}\right|+\left|\bar{\pi}_{ij}-\pi_{\rho^{-}}\right|+\left|\bar{\mu}_{ij}\nu_{\rho^{-}}-\mu_{\rho^{-}}\bar{\nu}_{ij}\right|\\ +\left|\bar{\mu}_{ij}\,\pi_{\rho^{-}}-\mu_{\rho^{-}}\bar{\pi}_{ij}\right|+\left|\bar{\nu}_{ij}\,\pi_{\rho^{-}}-\nu_{\rho^{-}}\bar{\pi}_{ij}\right|\\ +\left(\left|\min\left\{\bar{\mu}_{ij},\nu_{\rho^{-}}\right\}-\min\left\{\mu_{\rho^{-}},\bar{\nu}_{ij}\right\}\right|+\left|\max\left\{\bar{\mu}_{ij},\nu_{\rho^{-}}\right\}-\max\left\{\mu_{\rho^{-}},\bar{\nu}_{ij}\right\}\right|\right)\\ +\left(\left|\min\left\{\bar{\mu}_{ij},\pi_{\rho^{-}}\right\}-\min\left\{\mu_{\rho^{-}},\bar{\pi}_{ij}\right\}\right|+\left|\max\left\{\bar{\mu}_{ij},\pi_{\rho^{-}}\right\}-\max\left\{\mu_{\rho^{-}},\bar{\pi}_{ij}\right\}\right|\right)\\ +\left(\left|\min\left\{\bar{\nu}_{ij},\pi_{\rho^{-}}\right\}-\min\left\{\nu_{\rho^{-}},\bar{\pi}_{ij}\right\}\right|+\left|\max\left\{\bar{\nu}_{ij},\,\pi_{\rho^{-}}\right\}-\max\left\{\nu_{\rho^{-}},\bar{\pi}_{ij}\right\}\right|\right)\end{array}\right], \quad (11)$$

wherein $\bar{x}_{ij}=\left(\bar{\mu}_{ij},\bar{\nu}_{ij}\right)$ and $\rho^{-}=\left(\mu_{\rho^{-}},\nu_{\rho^{-}}\right)=(0,1)$.

Step 4b: Using Eq. (10)-Eq. (11), we make a relative closeness-decision matrix (RC-DM) $\psi = (\beta_j)_{1\times n}$, wherein

$$\beta_j=\frac{D\left(\bar{x}_{ij},\rho^{-}\right)}{D\left(\bar{x}_{ij},\rho^{-}\right)+D\left(\bar{x}_{ij},\rho^{+}\right)}, \quad (12)$$

and $$D\left(\bar{x}_{ij},\rho^{-}\right)=\frac{1}{m}\left(d\left(\bar{x}_{1j},\rho^{-}\right)+d\left(\bar{x}_{2j},\rho^{-}\right)+d\left(\bar{x}_{3j},\rho^{-}\right)\ldots+d\left(\bar{x}_{mj},\rho^{-}\right)\right),$$

$$D\left(\bar{x}_{ij},\rho^{+}\right)=\frac{1}{m}\left(d\left(\bar{x}_{1j},\rho^{+}\right)+d\left(\bar{x}_{2j},\rho^{+}\right)+d\left(\bar{x}_{3j},\rho^{+}\right)\ldots+d\left(\bar{x}_{mj},\rho^{+}\right)\right),\ j=1,2,\ldots,n.$$

Step 4c: Finding the objective weight (w_j^o) from Eq. (13) as

$$w_j^o=\frac{\beta_j}{\sum_{j=1}^{n}\beta_j},\quad j=1,2,\ldots,n. \quad (13)$$

Case II: Subjective weight of criteria by IF-RANCOM approach.

This approach includes subsequent procedure as

Step 4d: Linguistic values of criteria for expert panels are defined and changed into IFNs. We create an aggregated matrix to evaluate the performance of each criterion using Eq. (2).

Step 4e: With the use of proposed IF-score function, we find an IF-score value of each aggregated IFN for each criterion and form a column matrix $\Omega = (\eta_j)_{1\times n}$, $j = 1, 2, \ldots, n$, where

$$\eta_j=\frac{1}{2(e+1)}\left(\sqrt{\mu_j}\,e^{\left(\sqrt{\mu_j}\right)}+\sqrt{1-\nu_j}\,e^{\left(\sqrt{1-\nu_j}\right)}+\left(\sqrt{\mu_j}+\sqrt{1-\nu_j}\right)\sqrt{\frac{1+\mu_j-\nu_j}{2}}\right), \quad (14)$$

Step 4f: Considering the IF-score ratings, we estimate the preference order of defined criteria.

Step 4g: Based on the pairwise assessment of criteria, create a ranking comparison matrix (RCM) $C = (\theta_{lj})_{n\times n}$, $j = 1, 2, \ldots, n$, as

$$\theta_{lj} = \begin{array}{c} \\ R_1 \\ R_2 \\ \vdots \\ R_n \end{array} \begin{array}{c} \begin{array}{cccc} R_1 & R_2 & \cdots & R_n \end{array} \\ \begin{bmatrix} \delta_{11} & \delta_{11} & \cdots & \delta_{1n} \\ \delta_{21} & \delta_{22} & \cdots & \delta_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \delta_{n1} & \delta_{n2} & \cdots & \delta_{nn} \end{bmatrix} \end{array}, \text{ where } \delta_{lj} = \begin{cases} 1, & if\ S(R_j) < S(R_l), \\ 0.5, & if\ S(R_j) = S(R_l), \\ 0, & if\ S(R_j) > S(R_l). \end{cases} \tag{15}$$

Here, the comparison result is presented by δ_{ij}.

Step 4h: Determination of summed criteria weight (SCW) of criteria as

$$Q_j = \sum_{t=1}^{n} \theta_{lj},\ j = 1, 2, \ldots, n. \tag{16}$$

Step 4i: Finding the subjective weight of criteria as

$$w_j^s = \frac{Q_j}{\sum_{j=1}^{n} Q_j},\ j = 1, 2, \ldots, n. \tag{17}$$

Case III: Calculation of combined weight of criteria by IF-modified RCC-RANCOM model.

In this process, we integrate objective and subjective weights obtained through IF-modified RCC and IF-RANCOM models, respectively. Thus, the combined weighting formula is defined as

$$w_j = \gamma w_j^o + (1-\gamma) w_j^s,\ j = 1, 2, \ldots, n. \tag{18}$$

wherein $\gamma \in [0,1]$ is weighting precision coefficient.

Step 5: Normalize an A-IFDM.

In this step, the normalized A-IFDM (NA-IFDM) $U = (\varepsilon_{ij})_{m\times n}$ from IF-score value of A-IFDM $Z = \mathbb{S}(\bar{x}_{ij})_{m\times n}$ is calculated by the normalization techniques, given as follows:

Step 5.1. This process abolishes the dimensions of criteria with linear sum-based procedure. Thus, the linear NA-IFDM $U^{(1)} = (\varepsilon_{ij}^{(1)})_{m\times n}$ is created by Eq. (19), where

$$\varepsilon_{ij}^{(1)} = \begin{cases} \mathbb{S}(\bar{x}_{ij}) \Big/ \sum_{i=1}^{m} \mathbb{S}(\bar{x}_{ij}),\ R_j \in R_b, \\ \left(1/\mathbb{S}(\bar{x}_{ij})\right) \Big/ \sum_{i=1}^{m} \left(1/\mathbb{S}(\bar{x}_{ij})\right),\ R_j \in R_n, \end{cases} \tag{19}$$

where R_b and R_n symbolize benefit and cost-type of criteria, respectively.

Step 5.2. This process uses the max operator and finds the normalized extended assessment matrix, i.e., NA-IFDM $U^{(2)} = (\varepsilon_{ij}^{(2)})_{m\times n}$ using Eq. (20), where

$$\varepsilon_{ij}^{(2)} = \begin{cases} \mathbb{S}(\bar{x}_{ij}) \Big/ \left(\max_{i\in F} \mathbb{S}(\bar{x}_{ij})\right),\ R_j \in R_b, \\ \left(1/\mathbb{S}(\bar{x}_{ij})\right) \Big/ \left(\max_{i\in F} \left(1/\mathbb{S}(\bar{x}_{ij})\right)\right),\ R_j \in R_n, \end{cases} \tag{20}$$

where F denotes the set of alternatives.

Step 5.3. This process utilizes the max-mix operator and gets the normalized extended assessment matrix, i.e., NA-IFDM $U^{(3)} = (\varepsilon_{ij}^{(3)})_{m\times n}$ via Eq. (21), where

$$\varepsilon_{ij}^{(3)} = \begin{cases} \dfrac{\mathbb{S}(\bar{x}_{ij}) - \min_{i\in F} \mathbb{S}(\bar{x}_{ij})}{\max_{i\in F} \mathbb{S}(\bar{x}_{ij}) - \min_{i\in F} \mathbb{S}(\bar{x}_{ij})}, & R_j \in R_b, \\ \dfrac{\max_{i\in F} \mathbb{S}(\bar{x}_{ij}) - \mathbb{S}(\bar{x}_{ij})}{\max_{i\in F} \mathbb{S}(\bar{x}_{ij}) - \min_{i\in F} \mathbb{S}(\bar{x}_{ij})}, & R_j \in R_n. \end{cases} \tag{21}$$

Step 5.4. Computation of overall normalized assessment matrix.

Combining the aforesaid normalized values by means of two parameters α and β, the averaged NA-IFDM $U = (\varepsilon_{ij})_{m\times n}$ is computed, where ε_{ij} is an IF-score value obtained using the following expression:

$$\varepsilon_{ij} = \alpha\varepsilon_{ij}^{(1)} + \beta\varepsilon_{ij}^{(2)} + (1-\alpha-\beta)\varepsilon_{ij}^{(3)}, \tag{22}$$

where ε_{ij} denotes the averaged NA-PF-DM. where $\alpha \in [0, 1]$, $\beta \in [0, 1]$ and these two balanced coefficients are estimated by DEs. In this work, we consider $\alpha = \beta = 1/3$.

Step 6: Evaluation of reference/average solution matrix (ASM).

The reference/average solution matrix is calculated, where the reference value ς_j is given by Eq. (23) as

$$\varsigma_j = \frac{1}{m}\sum_{i=1}^{m} \mathbb{S}(\varepsilon_{ij}),\ j = 1, 2, \ldots, n. \tag{23}$$

Step 7: Calculate the subordinate scores for each alternative.

This step computes the subordinate scores ($p_i^{(1)}$ and $p_i^{(2)}$) of i^{th} alternative by means of the distance between each option and the reference value, where $i = 1, 2, \ldots, m$. Here, we combine the arithmetic and geometric weighted operators for combining distances on each alternative and ASM in relation to all criteria.

$$p_i^{(1)} = \vartheta\left(\sum_{j=1}^{n} w_j\left(\varepsilon_{ij} - \varsigma_j\right)\right) + (1-\vartheta)\left(\frac{\prod_{t=1}^{n}\left(\varsigma_j - \varepsilon_{ij}\right)^{w_j}}{\prod_{s=1}^{n}\left(\varepsilon_{ij} - \varsigma_j\right)^{w_j}}\right), \tag{24}$$

From Eq. (24), it is combined best and worst performance of options over defined criteria. Here, t ($t = 1, 2, \ldots, n$) represents the part of criteria that holds $\varepsilon_{ij} < \varsigma_j$, and s ($s = 1, 2, \ldots, n$) represents the part of criteria that holds $\varepsilon_{ij} > \varsigma_j$. In addition, ϑ ($0 \leq \vartheta \leq 1$) denotes the preference parameter. If expert considers comprehensive performance of options, then higher rating of ϑ is taken, whereas expert considers individual performance of options, then smaller rating of ϑ is taken.

$$p_i^{(2)} = \phi \max_j\left(w_j\left(\varepsilon_{ij} - \varsigma_j\right)\right) + (1-\phi)\min_j\left(w_j\left(\varepsilon_{ij} - \varsigma_j\right)\right), \tag{25}$$

where $i = 1, 2, \ldots, m$ and $j = 1, 2, \ldots, n$. ϕ ($0 \le \phi \le 1$) is preference parameter. If the DEs consider the best performance of options, then higher rating of ϕ is taken, whereas DEs consider worst performance of options, then smaller rating of ϕ is taken.

Step 8: Computation of final comprehensive score (FCS) for each option.

In accordance with subordinate scores ($p_i^{(1)}$ and $p_i^{(2)}$) of i^{th} alternative, the FCS of i^{th} alternative is calculated by Eq. (26), where $i = 1, 2, \ldots, m$.

$$p_i = \frac{1}{2}\left(\frac{p_i^{(1)}}{\sqrt{\sum_{i=1}^{m}\left(p_i^{(1)}\right)^2}} + \frac{p_i^{(2)}}{\sqrt{\sum_{i=1}^{m}\left(p_i^{(2)}\right)^2}} \right). \tag{26}$$

For the precision and consistency of outcomes, we need to utilize normalization procedure to certify that proportions of subordinate scores $p_i^{(1)}$ and $p_i^{(2)}$ are identical. Since values of $p_i^{(1)}$ and $p_i^{(2)}$ may be negative, therefore, we implement vector normalization procedure, given in Eq. (26).

Step 9: On the basis of decreasing values of FCS (p_i), $i = 1, 2, \ldots, m$, prioritize the options. Higher the FCS (p_i) determines the best option.

4. EXPERIMENTAL RESULTS

This section first implements the proposed IF-modified RCC-RANCOM-MACONT method on a case study of CE interest areas evaluation problem in the agri-food sector. Further, sensitivity and comparative discussions are provided to test the validity of obtained results.

4.1. Case Study: Assessment of CE Interested Regions in the Agri-food Sector

Here, we present a case study related to CE interested regions assessment in the agri-food sector. By utilizing the proposed framework, we recognize CE interested regions that contribute to the sustainability perspectives of CE scheme in the agri-food sector. For this purpose, some CE areas of interest are taken for evaluation, which are Resource efficiency (F_1), Digital transformation (F_2), Circular business model (F_3), Supply chain management (F_4), Product life cycle management (F_5). To collect the data, we have conducted online and offline meetings with the DEs. Next, a committee is formed consisting of four DEs, who are having expertise in the agricultural sustainability, I4.0, CE and logistics management. Based on the discussion with experts' committee and analysis of the relevant literature, nine criteria are taken to evaluate the CE areas of interest in agri-food sector and specified in Table 2.

Table 2 Different types of sustainability criteria (Krstic et al. [15], Verdouw et al. [19]) for assessing CE interested regions in agri-food sector

Dimensions	Criteria	Description
Economic	Implementation costs (R1)	It comprises all the costs associated with learning how to use the technology and adapting it for specific purposes, purchasing equipment, software development, training of employees, etc.
	Operational costs (R2)	It refers to the costs related to logistics activities including ordering, packing, supply, collection, storage, shipping, etc.
	Material value preservation (R3)	It refers to the degree of preservation of the value of materials to minimize its value degradation and maximize its residual value, and consequently increase its utilization, life cycle, and the overall value.
Social	Health (R4)	It refers the degree of impact of logistics activities on the health of people.
	Safety (R5)	It refers to improve safety culture throughout the logistics network.
	Labor market (R6)	It considers the positive impact of CE interest area on the labor market.
Environmental	Waste reduction (R7)	It considers the role of the CE area of interest to waste reduction.
	Emissions reduction (R8)	It considers the role of the CE interest area to the reduction of emissions.
	Energy resource preservation (R9)	It refers the degree of preservation of non-renewable and renewable energy resources.

The implementation of IF-modified RCC-RANCOM-MACONT is discussed as follows.

Step 1: To assess the CE interested regions concerning the taken evaluation criteria, we adopt Table 3 from Tripathi et al. [52], which represents LVs and their corresponding IFNs. The DEs are asked to present the importance rating of alternatives using Table 3. Next, different opinions of four DEs are collected regarding the performance of each alternative area and created a LDM with regard to each criterion, and presented in Table 5.

Table 3 LVs and corresponding IFNs for assessing CE interested regions in agri-food sector

LVs	IFNs
Extremely high (EH)	(0.95, 0.05)
Very very high (VVH)	(0.85, 0.1)
Very high (VH)	(0.8, 0.15)
High (H)	(0.7, 0.2)
Moderate high (MH)	(0.6, 0.3)
Medium (M)	(0.5, 0.4)
Moderate low (ML)	(0.4, 0.5)
Low (L)	(0.3,0.6)
Very low (VL)	(0.2, 0.7)
Very very low (VVL)	(0.1, 0.8)
Extremely low (EL)	(0.05, 0.95)

Table 4 Linguistic decision opinions for assessing CE interested regions in agri-food sector

	F_1	F_2	F_3	F_4	F_5
R_1	(VVL,ML,L,M)	(VL,L,ML,ML)	(EL,VL,L,L)	(M,L,L,VL)	(ML,EL,L,VL)
R_2	(L,VL,ML,L)	(VL,ML,VL,M)	(VL,VL,VL,ML)	(VVL,ML,L,ML)	(L,ML,VL,VL)
R_3	(MH,L,ML,H)	(ML,ML,H,H)	(L,VVH,M,M)	(M,H,MH,VVH)	(L,VVH,ML,H)
R_4	(VH,M,H,ML)	(MH,H,VH,ML)	(M,VH,M,ML)	(ML,VVH,M,H)	(VH,L,MH,M)
R_5	(ML,M,H,MH)	(H,L,MH,MH)	(VL,H,MH,M)	(H,VVH,H,M)	(M,MH,VH,VH)
R_6	(M,ML,VVH,H)	(H,M,ML,VVH)	(ML,ML,H,VH)	(MH,M,M,H)	(MH,H,MH,M)
R_7	(M,MH,ML,MH)	(MH,MH,H,VH)	(ML,M,EH,H)	(M,MH,ML,H)	(H,M,H,MH)
R_8	(H,ML,VVH,ML)	(VH,M,ML,MH)	(L,ML,MH,MH)	(M,H,M,VH)	(M,H,MH,VH)
R_9	(M,H,MH,M)	(L,MH,MH,M)	(H,MH,M,VVH)	(VVH,H,M,H)	(MH,VH,VH,M)

Step 2: With the utilization of Table 2 and Table 3, the linguistic significance ratings of DEs are assigned as per their skills, expertise and knowledge and given in Table 4. From Eq. (6)-Eq. (8), weight of expert is calculated and mentioned in Table 5.

Table 5 Weight of DEs for assessing CE interested regions in agri-food sector

DEs	B_1	B_2	B_3	B_4
LVs	VH	VVH	VH	EH
a_k	0.228	0.252	0.228	0.291
a_k^r	0.138	0.241	0.138	0.483
λ_k	0.183	0.247	0.183	0.387

Step 3: To obtain the group decision opinion regarding the performance of each CE interested regions, we use Eq. (9) to create an A-IFDM in Table 6.

Step 4: For determining an objective weight of indicators using IF-modified RCC model, the first step is to measure PDM and NDM. Based on Eq. (10), we find PDM $d\left(\overline{x}_{ij},\rho^{+}\right)$ between an aggregated element $\overline{x}_{ij}$ and IF-IS $\rho^{+} = (1, 0)$, given as 0.674, 0.658, 0.341, 0.371, 0.357, 0.331, 0.334, 0.356 and 0.332. Next, we calculate the NDM $d\left(\overline{x}_{ij},\rho^{-}\right)$ between an aggregated element $\overline{x}_{ij}$ and IF-AIS $\rho^{-} = (0, 1)$ through Eq. (11), and presented as 0.366, 0.386, 0.699, 0.668, 0.684, 0.709, 0.704, 0.682 and 0.706. The RC-DM is derived via Eq. (12) and given as $\beta_1 = 0.352$, $\beta_2 = 0.37$, $\beta_3 = 0.672$, $\beta_4 = 0.643$, $\beta_5 = 0.657$, $\beta_6 = 0.682$, $\beta_7 = 0.678$, $\beta_8 = 0.657$ and $\beta_9 = 0.68$. From Eq. (13), an objective weight of criteria is estimated as w_j^o = (0.0653, 0.0686, 0.1246, 0.1193, 0.1219, 0.1265, 0.1258, 0.1219, 0.1261).

To find subjective weight of each criterion, an IF-RANCOM tool is used. In the following, each expert presents his/her views concerning assessment of each considered criterion and changed into an aggregated IFN using Eq. (2). Next, the score values of criterion are determined via Eq. (14) and accordingly ranked them. Table 7 presents an IF-score value and preference of each criterion, respectively.

Table 6 Aggregated IFDM to identify the most potential CE interest areas in the agri-food sector

Criteria	F_1	F_2	F_3	F_4	F_5
R_1	(0.381, 0.517)	(0.343, 0.556)	(0.235, 0.678)	(0.307, 0.591)	(0.227, 0.69)
R_2	(0.297, 0.603)	(0.379, 0.519)	(0.284, 0.615)	(0.335, 0.563)	(0.273, 0.626)
R_3	(0.557, 0.334)	(0.596, 0.297)	(0.605, 0.306)	(0.734, 0.187)	(0.665, 0.244)
R_4	(0.587, 0.321)	(0.616, 0.291)	(0.572, 0.342)	(0.685, 0.226)	(0.559, 0.35)
R_5	(0.568, 0.328)	(0.564, 0.33)	(0.539, 0.354)	(0.692, 0.22)	(0.719, 0.213)
R_6	(0.656, 0.251)	(0.705, 0.215)	(0.655, 0.265)	(0.606, 0.29)	(0.594, 0.303)
R_7	(0.551, 0.347)	(0.710, 0.213)	(0.722, 0.218)	(0.598, 0.297)	(0.620, 0.278)
R_8	(0.59, 0.315)	(0.599, 0.311)	(0.51, 0.386)	(0.691, 0.231)	(0.703, 0.219)
R_9	(0.577, 0.32)	(0.517, 0.381)	(0.73, 0.192)	(0.71, 0.2)	(0.676, 0.249)

Table 7 An aggregated IFN and preferences of criteria for assessing CE interested regions in agri-food sector

Criteria	B_1	B_2	B_3	B_4	Aggregated IFN	Crisp value	Rank
R_1	VVH	M	ML	L	(0.528, 0.378)	0.391	9
R_2	VH	H	M	ML	(0.6, 0.307)	0.452	8
R_3	VH	M	H	M	(0.615, 0.294)	0.464	7
R_4	MH	ML	VH	VH	(0.702, 0.229)	0.535	3
R_5	L	M	H	VVH	(0.696, 0.222)	0.536	1.5
R_6	H	MH	M	VH	(0.698, 0.225)	0.536	1.5
R_7	L	VH	ML	H	(0.64, 0.269)	0.487	6
R_8	M	H	VVH	MH	(0.676, 0.234)	0.521	5
R_9	MH	VH	M	H	(0.686, 0.228)	0.529	4

Next, an RCM is constructed using Eq. (15). In accordance with an RCM, the SCWs are computed using Eq. (16). Lastly, we obtain subjective weight of criteria with Eq. (17). Table 8 presents the required computational steps of the IF-RANCOM model.

By utilizing Eq. (18), the combined weight of criteria is computed as a sum of γ multiplied by objective weight of and the complement of γ i.e., (1- γ) multiplied by the subjective weight of criteria. For γ = 0.5 combined weight of criteria is estimated and presented as w_j = (0.0388, 0.0528, 0.0932, 0.1399, 0.1597, 0.162, 0.1061, 0.1165, 0.131).

Table 8 Results of IF-RANCOM model for assessing CE interested regions in the agri-food sector

Criteria	RCM									Q_j	w_j^s
	R_1	R_2	R_3	R_4	R_5	R_6	R_7	R_8	R_9		
R_1	0.5	0	0	0	0	0	0	0	0	0.5	0.0123
R_2	1	0.5	0	0	0	0	0	0	0	1.5	0.037
R_3	1	1	0.5	0	0	0	0	0	0	2.5	0.0617
R_4	1	1	1	0.5	0	0	1	1	1	6.5	0.1605
R_5	1	1	1	1	0.5	0.5	1	1	1	8	0.1975
R_6	1	1	1	1	0.5	0.5	1	1	1	8	0.1975
R_7	1	1	1	0	0	0	0.5	0	0	3.5	0.0864
R_8	1	1	1	0	0	0	1	0.5	0	4.5	0.1111
R_9	1	1	1	0	0	0	1	1	0.5	5.5	0.1358

Next, Fig. 2 exhibits the significance values of considered criteria for assessing CE interested regions in the agri-food sector. Labor market (R6) (0.162) is the most significant criterion, safety (R5) (0.1597) is the second most significant criterion, health (R4) (0.1399) is third, energy resource preservation (R9) (0.131) is fourth and emissions reduction (R8) (0.1165) is fifth most vital criteria for assessing CE interested regions in the agri-food sector.

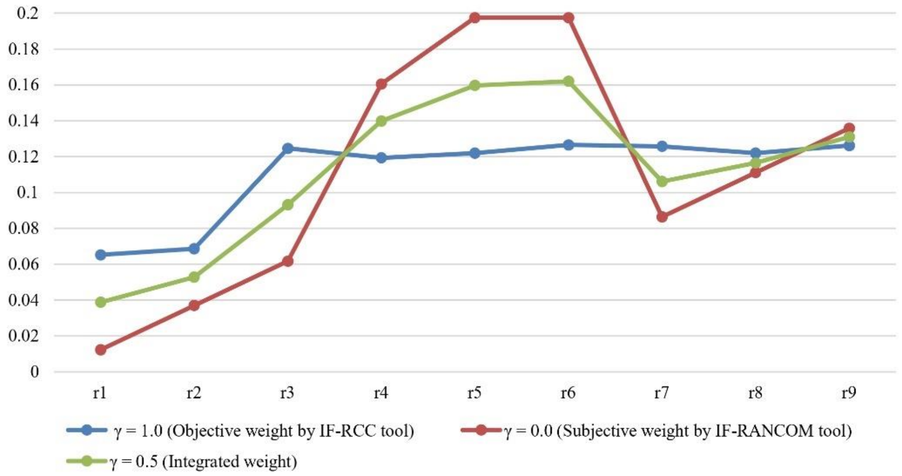

Fig. 2 Weights of considered criteria for CE interested regions in agri-food sector

Step 5: From Eq. (19)-Eq. (22) and Table 6, we determine the first, second, third and averaged normalized A-IFDM, and presented in Tables 9 and 10. For averaged NA-IFDM, we took $\alpha = \beta = 1/3$.

Step 6: Based on Table 10 and Eq. (23), we calculate reference/average solution matrix $F_0 = (\varsigma_j)_{1\times 9}$ and rating ς_j, (j = 1, 2, …, 9) of options over each criterion as follows: $\varsigma_1 = 0.5131$, $\varsigma_2 = 0.5709$, $\varsigma_3 = 0.4809$, $\varsigma_4 = 0.4691$, $\varsigma_5 = 0.4956$, $\varsigma_6 = 0.511$, $\varsigma_7 = 0.5436$, $\varsigma_8 = 0.5383$ and $\varsigma_9 = 0.5474$.

Table 9 First and second normalized A-IFDM for assessing CE interested regions in agri-food sector

	First Normalization					Second Normalization				
	F_1	F_2	F_3	F_4	F_5	F_1	F_2	F_3	F_4	F_5
R_1	0.154	0.1698	0.2404	0.188	0.2483	0.619	0.684	0.968	0.7558	1.0
R_2	0.208	0.1659	0.2159	0.186	0.2239	0.929	0.741	0.964	0.8316	1.0
R_3	0.175	0.1881	0.1881	0.238	0.2114	0.733	0.791	0.791	1.0	0.888
R_4	0.193	0.2047	0.1867	0.233	0.1827	0.832	0.881	0.803	1.0	0.786
R_5	0.183	0.1814	0.1726	0.228	0.2353	0.776	0.771	0.734	0.9695	1.0
R_6	0.205	0.2218	0.2018	0.188	0.1835	0.924	1.0	0.91	0.8480	0.827
R_7	0.169	0.2245	0.2256	0.187	0.194	0.751	0.995	1.0	0.8268	0.86
R_8	0.189	0.1916	0.1623	0.226	0.231	0.82	0.83	0.703	0.9776	1.0
R_9	0.177	0.1568	0.2315	0.226	0.2087	0.765	0.677	1.0	0.9754	0.902

Table 10 Third and combined normalized A-IFDM for assessing CE interested regions in agri-food sector

	Third Normalization					Combined Normalization				
	F_1	F_2	F_3	F_4	F_5	F_1	F_2	F_3	F_4	F_5
R_1	0.0	0.248	0.946	0.475	1.0	0.258	0.367	0.718	0.473	0.749
R_2	0.782	0.0	0.894	0.42	1.0	0.64	0.302	0.692	0.479	0.741
R_3	0.0	0.215	0.215	1.0	0.582	0.303	0.398	0.398	0.746	0.561
R_4	0.214	0.442	0.079	1.0	0.0	0.413	0.509	0.356	0.744	0.323
R_5	0.158	0.141	0.0	0.886	1.0	0.372	0.365	0.302	0.694	0.745
R_6	0.558	1.0	0.477	0.121	0.0	0.562	0.741	0.529	0.386	0.337
R_7	0.0	0.979	1.0	0.305	0.438	0.307	0.733	0.742	0.44	0.497
R_8	0.393	0.427	0.0	0.925	1.0	0.467	0.483	0.288	0.709	0.744
R_9	0.273	0.0	1.0	0.924	0.695	0.405	0.278	0.744	0.708	0.602

Step 7: From Eq. (24)-Eq. (25) and Table 10, we compute two subordinate scores $p_i^{(1)}$ and $p_i^{(2)}$, i = 1, 2, 3, 4, 5, of each option (for $\vartheta = 0.5$ and $\phi = 0.5$) as $p_1^{(1)} = 0.1288$, $p_2^{(1)} = 0.3409$, $p_3^{(1)} = 0.6275$, $p_4^{(1)} = 0.5826$, $p_5^{(1)} = 0.6728$, $p_1^{(2)} = -0.0084$, $p_2^{(2)} = 0.001$, $p_3^{(2)} = -0.0026$, $p_4^{(2)} = 0.0091$ and $p_5^{(2)} = 0.0058$.

Step 8: Based on Eq. (26), the final comprehensive score (FCS) p_i, i = 1, 2, 3, 4, 5, of each CE interest area is computed as $p_1 = -0.2451$, $p_2 = 0.1835$, $p_3 = 0.1814$, $p_4 = 0.5909$ and $p_5 = 0.5026$.

Step 9: Rank the alternatives based on obtained FCSs $p_1 = -0.2451$, $p_2 = 0.1835$, $p_3 = 0.1814$, $p_4 = 0.5909$ and $p_5 = 0.5026$. Thus, "Supply chain management (F_4) is the most potential CE interested regions contribute to the sustainability development of CE structure in agri-food sector and the prioritization ordering of CE interested regions is $F_4 \succ F_5 \succ F_2 \succ F_3 \succ F_1$.

4.2. Sensitivity Investigation

This section analyses the impacts of criteria weighting parameter on the final results. To this aim, we present the following cases

Case I *(Objective weight shuffling):* Considering the IF-modified RCC model in place of integrated IF-modified RCC-RANCOM, i.e., we are taking $\gamma = 1.0$ in Eq. (18) to assess the CE interested regions in the agri-food sector. Using an IF-modified RCC tool, the FCSs of CE interest areas are calculated and presented as $p_1 = -0.3258$, $p_2 = 0.0425$, $p_3 = 0.1808$, $p_4 = 0.5079$ and $p_5 = 0.4703$. Corresponding to decreasing ratings of FCSs, the ranking order of CE interested regions as $F_4 \succ F_5 \succ F_2 \succ F_3 \succ F_1$, and the "supply chain management (F_4)" is the most potential area among a set of CE regions of interest with respect to nine criteria.

Case II *(Subjective weight shuffling):* This case obtains the FCSs of CE interested regions in agri-food sector by taking subjective weight instead of combined objective-subjective weight of indicators, i.e., we are putting $\gamma = 0.0$ in Eq. (18). Using the subjective weighting IF-RANCOM method, the FCSs of CE interested regions in agri-food sector are computed and given as $p_1 = -0.163$, $p_2 = 0.3142$, $p_3 = 0.0898$, $p_4 = 0.6017$ and $p_5 = 0.4847$. Thus, the prioritization order of considered CE interested regions in the agri-food sector is

$F_4 \succ F_5 \succ F_2 \succ F_3 \succ F_1$, and the "supply chain management (F_4)" is the most suitable choice in relation to given evaluation criteria.

Case III *(Integrated weight shuffling):* Considering the combined IF-modified RCC-RANCOM approach, i.e., $\gamma = 0.5$ in Eq. (18), the FCSs of CE interested regions in agri-food sector are calculated as $p_1 = -0.2451$, $p_2 = 0.1835$, $p_3 = 0.1814$, $p_4 = 0.5909$ and $p_5 = 0.5026$. By means of decreasing values of FCSs, the prioritization order of CE interested regions in agri-food sector is $F_4 \succ F_5 \succ F_2 \succ F_3 \succ F_1$ and hence, "supply chain management (F_4)" is the most optimal choice for the given data set. Fig. 3 present required outcomes in relation to the weighting factor (γ).

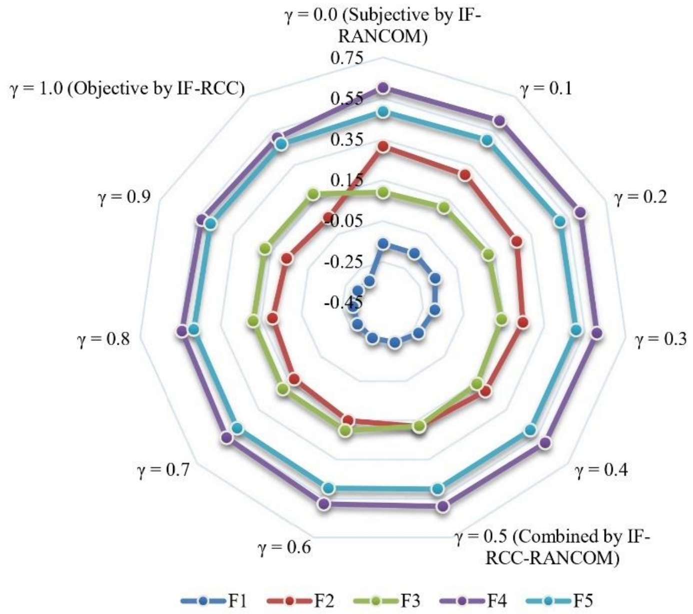

Fig. 3 Variation of FCSs of CE interested regions w.r.t. different values of factor (γ)

4.3. Comparative Study

This subsection performs comparative study to analyze rationality of proposed ranking approach in comparison with existing IF-MCDM models, given by Mardani et al.'s IF-COPRAS [53], Komal's WASPAS method [54], Qin et al.'s IF-TOPSIS model [55] and Tripathi et al.'s IF-CoCoSo [52]. To this aim, we have applied these extant methods on aforesaid case study of SEP sites selection problem.

4.3.1. IF-COPRAS Method

Using the IF-COPRAS [53] on abovementioned case study of CE interested regions assessment, we first compute the maximization and minimization indices, which are denoted as s_i and t_i, respectively. The computed values are $s_1 = (0.554, 0.347)$, $s_2 = (0.586, 0.320)$, $s_3 = (0.590, 0.323)$, $s_4 = (0.639, 0.268)$, $s_5 = (0.616, 0.297)$, $t_1 = (0.554, 0.347)$, $t_2 = (0.068, 0.911)$, $t_3 = (0.090, 0.885)$, $t_4 = (0.075, 0.902)$ and $t_5 = (0.093, 0.882)$. With the use of score function (Xu et al. [42]), the score values of maximization and minimization indices are computed as $S_{XW}(s_1) = 0.604$, $S_{XW}(s_2) = 0.633$, $S_{XW}(s_3) = 0.633$, $S_{XW}(s_4) = 0.686$, $S_{XW}(s_1) = 0.659$, $S_{XW}(t_1) = 0.085$, $S_{XW}(t_2) = 0.078$, $S_{XW}(t_3) = 0.103$, $S_{XW}(t_4) = 0.087$ and $S_{XW}(t_5) = 0.106$. Further, relative degree (RD) of each interested region is obtained as 0.3505, 0.3695, 0.3571, 0.3906 and 0.369, and finally, a UD of alternative is estimated as 89.75%, 94.6%, 91.43%, 100.00% and 94.48%. Corresponding to the decreasing ratings of UDs, prioritization of CE interested regions in the agri-food sector is $F_4 \succ F_2 \succ F_5 \succ F_3 \succ F_1$ and thus, "supply chain management (F_4)" is the best region of interest among the set of five CE interested regions in agri-food sector.

4.3.2. IF-WASPAS Method

By applying IF-WASPAS method [54] on the aforesaid case study, the additive importance ($c_i^{(1)}$) using weighting sum model is computed as $c_1^{(1)} = (0.587, 0.313)$, $c_2^{(1)} = (0.614, 0.292)$, $c_3^{(1)} = (0.627, 0.286)$, $c_4^{(1)} = (0.666, 0.242)$ and $c_5^{(1)} = (0.652, 0.262)$. Next, the multiplicative importance ($c_i^{(2)}$) using weighted product model is determined as $c_1^{(2)} = (0.585, 0.316)$, $c_2^{(2)} = (0.604, 0.300)$, $c_3^{(2)} = (0.614, 0.296)$, $c_4^{(2)} = (0.66, 0.247)$ and $c_5^{(2)} = (0.645, 0.267)$. Using Xu et al.'s score function (Xu et al. [42]) the score values of additive and multiplicative importance values are calculated and shown as $S_{XW}(c_1^{(1)})$ 0.637, $S_{XW}(c_2^{(1)}) = 0.661$, $S_{XW}(c_3^{(1)}) = 0.67$, $S_{XW}(c_4^{(1)}) = 0.712$, $S_{XW}(c_5^{(1)}) = 0.695$, $S_{XW}(c_1^{(2)}) = 0.635$, $S_{XW}(c_2^{(2)}) = 0.652$, $S_{XW}(c_3^{(2)}) = 0.659$, $S_{XW}(c_4^{(2)}) = 0.707$ and $S_{XW}(c_5^{(2)}) = 0.689$. Lastly, total significance of each CE interest area is estimated as the arithmetic mean of additive and multiplicative significance values and given as 0.6358, 0.6564, 0.6647, 0.7096 and 0.6919. Thus, the ranking order of CE interested regions in agri-food sector is $F_4 \succ F_5 \succ F_3 \succ F_2 \succ F_1$ and the "supply chain management (F_4)" is the best choice for considered data set.

4.3.3. IF-TOPSIS Method

By applying IF-TOPSIS method [55] on abovementioned case study of CE interested regions assessment in agri-food sector, we compute the best and worst values from A-IFDM and obtains as $\phi_j^+ = \{(0.227, 0.690), (0.273, 0.626), (0.734, 0.187), (0.685, 0.226), (0.719, 0.213), (0.705, 0.215), (0.722, 0.218), (0.703, 0.219), (0.730, 0.192)\}$ and $\phi_j^+ = \{(0.381, 0.517), (0.379, 0.519), (0.557, 0.334), (0.559, 0.350), (0.539, 0.354), (0.594, 0.303), (0.551, 0.347), (0.510, 0.386), (0.517, 0.381)\}$. Using the similarity measure, relative closeness rating (RCR) of each CE interested region is estimated as 0.2504, 0.3849, 0.4524, 0.7242 and 0.6278, respectively. Hence, the preference order of CE interested regions in agri-food sector is $F_4 \succ F_5 \succ F_3 \succ F_2 \succ F_1$ and "supply chain management (F_4)" is the best choice among a set of five CE interested regions in agri-food sector.

Fig. 4 presents the acquired ranking results by the proposed and extant IF-MCDM methods. As per the obtained results, we found that the preference ranks of CE interest areas by the developed IF-modified RCC-RANCOM-MACONT approach is slightly different from the Mardani et al.'s IF-COPRAS [53], Komal's WASPAS method [54], Qin et al.'s IF-TOPSIS model [55] and Tripathi et al.'s IF-CoCoSo [52], while the most suitable choice "Supply chain management (F_4)" is the same by all the IF-MCDM models. From Fig. 5, the Spearman's rank correlation coefficient (SRCC) is higher than 0.9 for each existing approach with the developed ranking framework. Moreover, the WS-coefficient

(Sałabun and Urbaniak [56]) is are higher than 0.85 for each existing approach with the developed ranking framework. The benefit of WS-coefficient describes the similarity degree of preference order of options, which illustrates the consistency of prioritization of CE interested regions in agri-food sector, is high (Mishra et al. [57], Biswas et al. [58], Jafar et al. [59], Ullah and Shah [60]). Accordingly, it can be observed that there is very robust association between prioritization outcomes. Also, the generalization and flexibility discussed by the developed IF-modified RCC-RANCOM-MACONT framework are lacking in the existing methods.

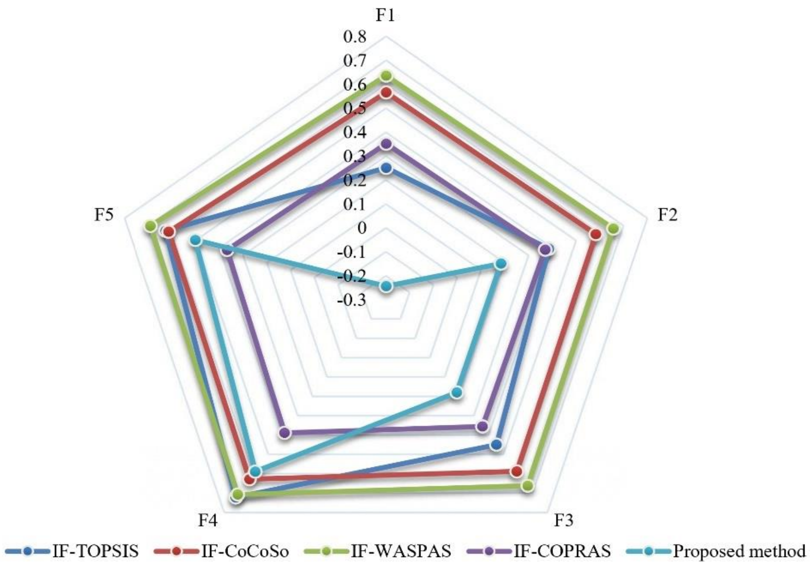

Fig. 4 Ranking orders of CE interested regions in the agri-food sector by different IF-MCDM models

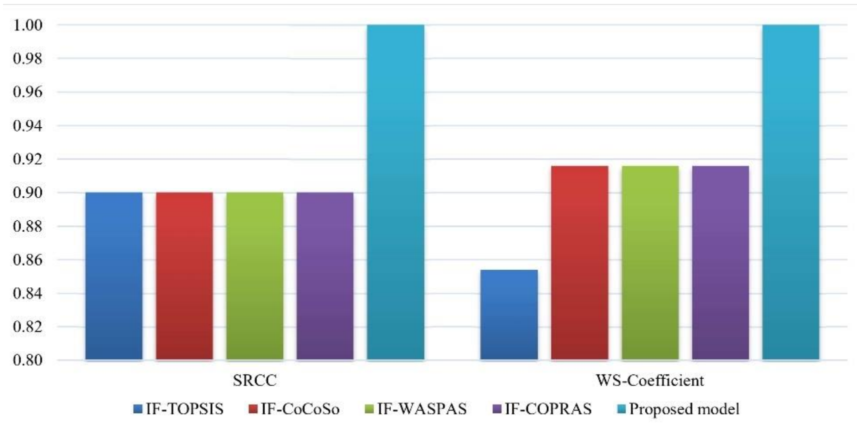

Fig. 5 Variation of SRCC and WS-coefficient of the proposed method with different existing approaches

4.3.4. IF-CoCoSo Method

This model first computes the additive and multiplicative importance of alternatives, which are similar as IF-WASPAS model [54]. Based on additive and multiplicative importance, the relative compromise ratings are determined as $t_1^{(1)} = 0.1893$, $t_2^{(1)} = 0.1955$, $t_3^{(1)} = 0.1979$, $t_4^{(1)} = 0.2113$, $t_5^{(1)} = 0.206$, $t_1^{(2)} = 0.7773$, $t_2^{(2)} = 0.8026$, $t_3^{(2)} = 0.8127$, $t_4^{(2)} = 0.8676$, $t_5^{(2)} = 0.8459$, $t_1^{(3)} = 0.8959$, $t_2^{(3)} = 0.925$, $t_3^{(3)} = 0.9367$, $t_4^{(3)} = 1.0$ and $t_5^{(3)} = 0.975$. Finally, the overall compromise ratings of five CE interested regions in agri-food sector are estimated and given as 0.5649, 0.5832, 0.5906, 0.6305 and 0.6147, respectively. Based on decreasing ratings of overall compromise ratings, Thus, the ranking order of CE interested regions in agri-food sector is $F_4 \succ F_5 \succ F_3 \succ F_2 \succ F_1$ and "supply chain management (F_4)" is the best interested region among a set of five CE interested regions in agri-food sector.

Next, we present the advantages of developed IF-modified RCC-RANCOM-MACONT over the existing IF-MCDM models as follows:

- The developed IF-modified RCC-RANCOM-MACONT model utilizes new IF-score function, which avoids shortcomings of extant IF-score functions (Xu [41], Xu et al. [42], Zeng et al. [43], Feng et al. [44]).
- The proposed method uses new IF-distance measure, which overcomes drawbacks of extant IF-distance measures (Shen et al. [45], Tripathi et al. [46], Wu et al. [47], Ejegwa and Agbetayo [48], Li et al. [49]). The developed distance measure is implemented to compute distance matrix in criteria weighting procedure and further employed to determine the deviation from the normalized weighted evaluation values of alternatives to the reference point.
- The introduced model calculates the DEs' weights through new score function and rank reciprocal-based weighting procedure, while Qin et al.'s IF-TOPSIS [55] and Komal's IF-WASPAS [54] ignores the significance weight of DEs in the procedure of group decision-making.
- The proposed model computes weight of indicators through a collective objective-subjective weighting procedure combining the IF-modified RCC and the IF-RANCOM models for objective and subjective weights of indicators, which does not only estimate weight of indicators with given data but also involve the DEs' opinions during the criteria weighting procedure.

5. CONCLUSION

This paper aimed to develop a ranking framework for identifying the CE interested regions which are most affected by implementing the I4.0 technologies during the assessment of logistics process in agri-food sector. To this aim, we have assessed the performance of five CE interest areas including *Resource efficiency, Digital transformation, Circular business model, Supply chain management, Product life cycle management* with respect to nine criteria under the three dimensions of sustainability. In this framework, we have derived the weights of involved DEs using an integrated score function and rank reciprocal-based procedure. In the following, new IF-score function has been developed on IFSs with its efficiency over existing ones. Next, the group decision opinions have been aggregated into a single opinion regarding the performance value of each CE interest area on the basis of given criteria. Further, the criteria weights have been computed with integrated IF-modified RCC-RANCOM approach in which objective weight has been derived from IF-modified RCC tool, while the subjective weights have determined via IF-RANCOM procedure. To do so, new IF-distance measure has been given for IFSs with its efficiency over existing distance measures. Finally, a stepwise procedure of IF-modified RCC-RANCOM-MACONT methodology has been presented to rank the five CE interested regions in agri-food sector, which proves its effectiveness and practicality. The acquired result shows that a region "*supply chain management*" has highest final comprehensive score among a set of five CE interested regions over economic, social and environmental aspects of sustainability. Sensitivity assessment has been conducted to see the effect of criteria weighting coefficient on the final result. Lastly, a comparison with extant approaches has been made to test the effectiveness and robustness of proposed ranking framework.

This paper has some limitations, which are i) the developed IF-modified RCC-RANCOM-MACONT approach does not replicate the way to find the importance rating of DEs to determine the weight of DEs, and ii) One of key limitation of proposed method is its computational procedure, which is the outcomes of executing the modified RCC, RANCOM and MACONT approaches using the proposed IF-distance measure, IF-score function to estimate subordinate comprehensive scores of options. Further, deriving final comprehensive degrees of options and determine the prioritization the options. This complexity of IF-modified RCC-RANCOM-MACONT is a potentially protective characteristic for implementing by diverse DEs. In future studies, the IF-modified RCC-RANCOM-MACONT framework can be extended with several MCGDM models such as stochastic identification of weights (SITW), reference ideal method (RIM), characteristic object method (COMET), stable preference ordering towards ideal solution (SPOTIS), and so on. The developed IF-modified RCC-RANCOM-MACONT method can be extended with diverse uncertain environments, such as q-ROF-rough sets, linear Diphantine fuzzy, type-2 fuzzy sets, Pythagorean hypersoft sets and different types of linguistic term sets. In future, we can develop new methodologies to solve the interactive CE interested regions assessment in agri-food sector.

Acknowledgement: *The authors present their appreciation to King Saud University for funding this research through Researchers Supporting Project number (RSPD2024R533), King Saud University, Riyadh, Saudi Arabia.*

REFERENCES

1. Nurhasanah, N., Machfud, Mangunwidjaja, D., Romli, M., 2020, *A literature review on the design of intelligent supply chain for natural fibre agroindustry*, International Journal of Supply Chain Management, 9, pp. 182-197.
2. Li, L., 2024, *Mechanism Analysis of Smart Logistics Technology to Enhance the Logistics Efficiency of Rural E-Commerce*, Applied Mathematics and Nonlinear Sciences, 9(1), pp. 1-15.
3. Sun, X., Kuo, Y.-H., Xue, W., Li, Y., 2024, *Technology-driven logistics and supply chain management for societal impacts*, Transportation Research Part E: Logistics and Transportation Review, 185, 103523.
4. Bai, C., Sarkis, J., 2019, *Integrating and extending data and decision tools for sustainable third-party reverse logistics provider selection*, Comput. Oper. Res., 110, pp. 188–207.
5. Chen, Z.-S., Zhang, X., Govindan, K., Wang, X.-J., Chin, K.-S., 2021, *Third-party reverse logistics provider selection: A computational semantic analysis-based multi-perspective multi-attribute decision-making approach*, Expert Systems with Applications, 166, 114051.

6. Mishra, A. R., Rani, P., Pamucar, D., Saha, A., 2022, *A q-rung orthopair fuzzy combined compromise solution approach for selecting sustainable third-party reverse logistics provider*, Management Decision, 61(6), pp. 1816-1853.
7. Adegbola, K., 2023, *A simulation study of single-vendor, single and multiple-manufacturers supply chain system, with stochastic demand and two distribution policies*, Journal of Decision Analytics and Intelligent Computing, 3(1), pp. 62–79.
8. Sharma, V., Sharma, K., Kumar, M., Chatterjee, P., 2024, *Supply chain efficiency and performance measurement in the automotive sector: Content analysis and future research directions*, Journal of Decision Analytics and Intelligent Computing, 4(1), pp. 121–135.
9. Badi, I., Bouraima, M. B., Stević, Ž., Oloketuyi, E. A., Makinde, O. O., 2024, *Optimizing Vendor-Managed Inventory in Multi-Tier Distribution Systems*, Spectrum of Operational Research, 1(1), pp. 33-43.
10. Mahmood, T., Asif, M., ur Rehman, U., Ahmmad, J., 2024, *T-Bipolar Soft Semigroups and Related Results*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 258-271.
11. Farooque, M., Zhang, A., Thürer, M., Qu, T., Huisingh, D., 2019, *Circular supply chain management: a definition and structured literature review*, Journal of Cleaner Production, 228, pp. 882–900.
12. Lu, S., Zhu, L., Wang, Y., Xie, L., Su, H., 2020, *Integrated forward and reverse logistics network design for a hybrid assembly-recycling system under uncertain return and waste flows: A fuzzy multi-objective programming*, Journal of Cleaner Production 243, 118591.
13. Nobre, G.C., Tavares, E., 2021, *The quest for a circular economy final definition: a scientific perspective*, Journal of Cleaner Production, 314, 127973.
14. Adams, K. T., Osmani, M., Thorpe, T., Thornback, J., 2017, *Circular economy in construction: current awareness, challenges and enablers*, Proceedings of the Institution of Civil Engineers - Waste and Resource Management, 170(1), pp. 15–24.
15. Krstic, M., Agnusdei, G. P., Miglietta, P. P., Tadic, S., 2022, *Logistics 4.0 toward circular economy in the agri-food sector*, Sustainable Futures, 4, 100097.
16. Dwivedi, A., Chowdhury, P., Paul, S.K., Agrawal, D., 2023, *Sustaining circular economy practices in supply chains during a global disruption*, International Journal of Logistics Management, 34(3), pp. 644-673.
17. Barreto, L., Amaral, A., Pereira, T., 2017, *Industry 4.0 implications in logistics: an overview*, Procedia Manufacturing, 13, pp. 1245-1252.
18. Winkelhaus, S., Grosse, E. H., 2020, *Logistics 4.0: a systematic review towards a new logistics system*, International Journal of Production Research, 58(1), pp. 18-43.
19. Verdouw, C. N., Robbemond, R. M., Verwaart, T., Wolfert, J., Beulens, A. J. M., 2015, *A reference architecture for IoT-based logistic information systems in agri-food supply chains*, Enterprise Information Systems, 12(7), pp. 755-779.
20. Alamin, A., Rahaman, M., Mondal, S. P., 2024, *Geometric Approach for Solving First Order Non-Homogenous Fuzzy Difference Equation*, Spectrum of Operational Research, 2(1), pp. 61-71.
21. Kannan, J., Jayakumar, V., Pethaperumal, M., 2024, *Advanced Fuzzy-Based Decision-Making: The Linear Diophantine Fuzzy CODAS Method for Logistic Specialist Selection*, Spectrum of Operational Research, 2(1), pp. 41-60.
22. Gazi, K. H., Raisa, N., Biswas, A., Azizzadeh, F., Mondal, S. P., 2024, *Finding the Most Important Criteria in Women's Empowerment for Sports Sector by Pentagonal Fuzzy DEMATEL Methodology*, Spectrum of Decision Making and Applications, 2(1), pp. 28-52.
23. Eti, S., Dinçer, H., Yüksel, S., Gökalp, Y., 2024, *A New Fuzzy Decision-Making Model for Enhancing Electric Vehicle Charging Infrastructure*, Spectrum of Decision Making and Applications, 2(1), pp. 94-99.
24. Atanassov, K. T., 1986, *Intuitionistic fuzzy sets*, Fuzzy sets and Systems, 20(1), pp. 87-96.
25. Çelik, S., Peker, İ., Gök-Kısa, A. C., Büyüközkan, G., 2023, *Multi-criteria evaluation of medical waste management process under intuitionistic fuzzy environment: A case study on hospitals in Turkey*, Socio-Economic Planning Sciences, 86, 101499.
26. Asif, M., Ishtiaq, U., Argyros, I. K., 2024, *Hamacher Aggregation Operators for Pythagorean Fuzzy Set and its Application in Multi-Attribute Decision-Making Problem*, Spectrum of Operational Research, 2(1), pp. 27-40.
27. Bajaj, J., Kumar, S., 2023, *A new intuitionistic fuzzy correlation coefficient approach with applications in multi-criteria decision-making*, Decision Analytics Journal, 9, 100340.
28. Majumder, P., Bhowmik, P., Das, A., Senapati, T., Simic, V., Pamucar, D., 2023, *An intuitionistic fuzzy based hybrid decision-making approach to determine the priority value of indicators and its application to solar energy feasibility analysis*, Optik, 295, 171492.
29. Wan, S.-P., Dong, J.-Y., Chen, S.-M., 2024, *A novel intuitionistic fuzzy best-worst method for group decision making with intuitionistic fuzzy preference relations*, Information Sciences, 666, 120404.

30. Hussain, A., Ullah, K., 2024, *An Intelligent Decision Support System for Spherical Fuzzy Sugeno-Weber Aggregation Operators and Real-Life Applications*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 177-188.
31. Şahin, S., Koç, A., Sark, W. V., 2024, *Multi-criteria decision making for solar power - Wind power plant site selection using a GIS-intuitionistic fuzzy-based approach with an application in the Netherlands*, Energy Strategy Reviews 51, 101307.
32. Štilić, A, Puška A, Božanić, D, Đurić, A., 2024, *Ranking European Countries Using Hybrid MEREC-MARCOS MCDA Based on Travel and Tourism Development Index*, Tourism: An International Interdisciplinary Journal, 72(4), pp. 592-608.
33. Sahoo, S. K., Choudhury, B. B., Dhal, P. R., 2024, *A Bibliometric Analysis of Material Selection Using MCDM Methods: Trends and Insights*, Spectrum of Mechanical Engineering and Operational Research, 1(1), pp. 189-205.
34. Wen, Z., Liao, H., Zavadskas, E. K., 2020, *MACONT: Mixed Aggregation by Comprehensive Normalization Technique for Multi-Criteria Analysis*, Informatica, 31(4), pp. 857-880.
35. Truong, T., Li, Z., 2023, *Incorporated Dempster-Shafer Theory, MACONT, and e-STEP Method (DSM-eSTEP) for Multicriteria Tradeoff Analysis in Transportation Budget Allocation*, IEEE Access, 11, pp. 78522-78537.
36. Nguyen, A.-T., 2023, *Expanding the Data Normalization Strategy to the MACONT Method for Multi-Criteria Decision Making. Engineering*, Technology & Applied Science Research, 13(2), pp. 10489–10495.
37. Huang, S., Chen, H., 2023, *Research on quality evaluation of industry-education integration for rural vocational education in the perspective of rural revitalization with PL-MACONT method*, Journal of Intelligent & Fuzzy Systems, 44(6), pp. 9743-9755.
38. Chen, Z. Liang, W., S. Luo, S., 2024, *A Novel Integrated Picture Fuzzy MACONT Method and Its Application in Teaching Quality Evaluation in Higher Education*, IEEE Access 12, pp. 88345-88356.
39. Liang, Y., 2024, *An ExpTODIM-MACONT Based Multiple-Attribute Group Decision-Making Technique for Smart Classroom Teaching Evaluation of Basic English Under Interval-Valued Pythagorean Fuzzy Circumstances*, IEEE Access, 12, pp. 14130-14145.
40. Więckowski, J., Kizielewicz, B., Shekhovtsov, A., Sałabun, W., 2023, *RANCOM: a novel approach to identifying criteria relevance based on inaccuracy expert judgments*, Engineering Applications of Artificial Intelligence, 122, 106114.
41. Xu, Z. S., 2007, *Intuitionistic fuzzy aggregation operators*, IEEE Trans Fuzzy Syst, 15(6), pp. 1179–1187.
42. Xu, G. L., Wan, S. P., Xie, X. L., 2015, *A Selection Method Based on MAGDM with Interval-Valued Intuitionistic Fuzzy Sets*, Mathematical Problems in Engineering 2015, 791204.
43. Zeng, S., Chen, S.-M., Kuo, L.-W., 2019, *Multiattribute decision making based on novel score function of intuitionistic fuzzy values and modified VIKOR method*, Information Sciences, 488, pp. 76–92.
44. Feng, F., Zheng, Y., Alcantud, J. C., R., Wang, Q., 2020, *Minkowski Weighted Score Functions of Intuitionistic Fuzzy Values*, Mathematics, 8(7), 1143.
45. Shen, F., Ma, X., Li, Z., Xu, Z., Cai, D., 2018, *An extended intuitionistic fuzzy TOPSIS method based on a new distance measure with an application to credit risk evaluation*, Information Sciences, 428, pp. 105–119.
46. Tripathi, D.K., Nigam, S.K., Cavallaro, F., Rani, P., Mishra, A. R., Hezam, I. M., 2023, *A Novel CRITIC-RS-VIKOR Group Method with Intuitionistic Fuzzy Information for Renewable Energy Sources Assessment*, Group Decision and Negotiation, 32, pp. 1437-1468.
47. Wu, X., Song, Y., Wang, Y., 2021, *Distance-Based Knowledge Measure for Intuitionistic Fuzzy Sets with Its Application in Decision Making*, Entropy, 23(9), 1119.
48. Ejegwa, P. A., Agbetayo, J. M., 2023, *Similarity-Distance Decision-Making Technique and its Applications via Intuitionistic Fuzzy Pairs*, Journal of Computational and Cognitive Engineering 2(1), pp. 68-74.
49. Li, X., Liu, Z., Han, X., Liu, N., Yuan, W., 2023, *An Intuitionistic Fuzzy Version of Hellinger Distance Measure and Its Application to Decision-Making Process*, Symmetry, 15(2), 500.
50. Xu, Z. S., Chen, J., 2008, *An overview of distance and similarity measures of intuitionistic fuzzy sets*, International Journal of Uncertainty, Fuzziness and Knowledge-Based Systems, 16(04), pp. 529-555.
51. Szmidt, E., Kacprzyk, J., 2000, *Distances between intuitionistic fuzzy sets*, Fuzzy Sets and Systems, 114, pp. 505–518.
52. Tripathi, D. K., Nigam, S. K., Rani, P., Shah, A. R., 2023, *New intuitionistic fuzzy parametric divergence measures and score function-based CoCoSo method for decision-making problems*, Decision Making: Applications in Management and Engineering, 6(1), pp. 535–563.

53. Mardani, A., Devi, S., Alrasheedi, M., Arya, L., Singh, M. P, Pandey, K., 2024, *Hybrid Intuitionistic Fuzzy Entropy-SWARA-COPRAS Method for Multi-Criteria Sustainable Biomass Crop Type Selection*, Sustainability, 15(10), 7765.
54. Komal, 2023, *Archimedean t-norm and t-conorm based intuitionistic fuzzy WASPAS method to evaluate health-care waste disposal alternatives with unknown weight information*, Applied Soft Computing, 146, 110751.
55. Qin, Y., Rizk-Allah, R. M., Garg, H., Hassanien, A. E., Snášel, V., 2023, *Intuitionistic fuzzy-based TOPSIS method for multi-criterion optimization problem: a novel compromise methodology*, AIMS Mathematics 8(7), pp. 16825-16845.
56. Sałabun, W., Urbaniak, K., 2020, *A new coefficient of rankings similarity in decision-making problems*, In International Conference on Computational Science, pp. 632-645. Springer, Cham, https://doi.org/10.1007/978-3-030-50417-5_47
57. Mishra, A. R., Chandel, A., Saeidi, P., 2022, *Low-carbon tourism strategy evaluation and selection using interval-valued intuitionistic fuzzy additive ratio assessment approach based on similarity measures*, Environment Development & Sustainability, 24, pp. 7236-7282.
58. Biswas, A., Gazi, K. H., & Mondal, S. P., 2024, *Finding Effective Factor for Circular Economy Using Uncertain MCDM Approach*, Management Science Advances 1(1), pp. 31-52.
59. Jafar, M. N., Muniba, K., Saqlain, M., 2023, *Enhancing Diabetes Diagnosis through an Intuitionistic Fuzzy Soft Matrices-Based Algorithm*, Spectrum of Engineering and Management Sciences, 1(1), pp. 73-82.
60. Ullah, F., Shah, W. S., 2024, *Optimizing Multi-attributive Decision-making: A Novel Approach through Matrix Theory and Fuzzy Hypersoft Sets*, Spectrum of Engineering and Management Sciences, 2(1), pp. 100-109.