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Evaluating and Prioritizing Blockchain Networks Using Intuitionistic Fuzzy Multi-Criteria Decision-Making Method

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ABSTRACT

Being a generalization of fuzzy set, intuitionistic fuzzy set (IFS) obtains a better representation of fuzziness and uncertainty. Inspired by this concept, this paper first proposes a logarithmic distance measure to calculate the discrimination index between IFSs. Moreover, this work develops a hybrid ranking model by combining the distance measure, rank-sum model, Stepwise Weight Assessment Ratio Analysis (SWARA) weighting tool, Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) and VIseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methods under the context of intuitionistic fuzzy environment. In the proposed method, the rank-sum tool is utilized for deriving the decision makers' significance values, while the SWARA model is applied to evaluate the criteria weights. To show the practicality of introduced methodology, it is executed to a case study of determining the rank of blockchain networks in the healthcare management system. Comparative study is presented to confirm the advantages of proposed approach over the TOPSIS and VIKOR methods.

1. Introduction

Blockchain technology (BT) is a decentralized storage system that allows transparent, immutable, resistant information sharing within an organization. It refers to a chain of blocks where all blocks contain digital information, and each block is connected to its previous block [1]. Each block comprises a cryptographic hash of the data of the preceding block. As a shared, immutable and decentralized digital ledger, it facilitates the process of recording transactions and tracking assets in a business network [2]. By enabling decentralized systems, blockchain eradicates intermediaries, reduces transaction costs, and accelerates settlement times [3-4].

In the recent times, cyber security issues are the most pressing concerns for individuals, businesses, and governments throughout the world. The internet has made the world more interconnected as well as increased security risks, which are upward in scale and complexity. The execution of BT brings a substantial change to several domains, from finance to more general societal

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applications. In the literature, different factors are considered during the evaluation of BT in real-world problems. Sciarelli et al. [5] identified the factors affecting blockchain network in Italian firms and further evaluated their ranks during the implementation of blockchain. By means of organizational, ecological and technical dimensions, Li et al. [6] considered the criteria influencing blockchain networks in the building sectors. On the basis of extent survey, Siddiqui & Haroon [7] documented the critical issues during the assessment of BT execution and obtained their weights using ranking model. Considering different challenges, Pathak et al. [2] ranked the blockchain networks in healthcare using generalized fuzzy additive ratio assessment. With the involvement of multiple criteria and alternatives, the process of blockchain network selection is treated as a multi-criteria decision-making (MCDM) problem. MCDM methods can be more appropriate to deal with such types of decision analysis problems [8].

During the process of BT adoption, the given data may be uncertain [9]. To handle the uncertainty, Zadeh [10] developed the notion of fuzzy set (FS), which has been successfully executed to different domains. As a refinement of FS, Atanassov [11] linked the mechanisms and objects through membership grade (MG) and non-membership grade (NMG), and originated a new set, namely intuitionistic fuzzy set (IFS). The introduction of IFS theory into MCDM methods has augmented the practical potential and presented new insights for handling real-world problems with intuitionistic fuzzy (IF) information. To quantify the correlation between IFSs, Bajaj & Kumar [12] introduced an innovation correlation measure with its application in clustering, medical diagnosis, and pattern recognition. Mishra et al. [13] evaluated the wastewater treatment machineries using generalized IF-multi-attribute ideal-real comparative analysis. Hussain & Ullah [14] combined the individual information through proposed Sugeno-Weber aggregation operators and further presented its application. In accordance with the combination of best worst method and IF-preference relations, Wan et al. [15] developed a non-linear programming method for solving decision-making problems. Based on the literature survey, we found that there is no study for evaluating the blockchain networks in the healthcare sector using IF information-based methodology.

In the context of intuitionistic fuzzy environment, the "*Technique for Order Preference by Similarity to Ideal Solution* (TOPSIS)" and "*VIseKriterijumska Optimizacija I Kompromisno Resenje* (VIKOR)" approaches have been frequently employed for various perspectives. Using IF-information, Rouyendegh et al. [16] used the TOPSIS method for assessing the green suppliers in the supply chain management. Roszkowska et al. [17] utilized the IF-TOPSIS method to handle the issue of aggregating respondents' thoughts obtained by official statistics. On the basis of centroid coordinate representation, Sun et al. [18] proposed a novel distance measure-based IF-TOPSIS approach and its applicability in real-life problems. In a study, multi-objective transportation problem has been solved by IF-TOPSIS model [19]. While Krishankumar et al. [20] utilized the IF-VIKOR approach for solving personnel selection problem. Dağıstanlı [21] analyzed the performance of generalized IF-VIKOR method in the assessment of defense industry projects. Kansal & Kumar [22] studied the similarity and knowledge measures-based IF-VIKOR model and applied to select an appropriate adsorbent for removing hexavalent chromium from wastewater, whereas Liang & Liu [23] used the IF-VIKOR for shared manufacturing services assessment. Combining the aspects of TOPSIS and VIKOR approaches, this paper presents a novel MCDM method and utility in the assessment of blockchain network selection. In the literature, we found only one study by Sedady & Beheshtinia [24], who have combined these methods and named as TOPKOR model. The novel contributions of this work are listed as follows:

i. A new distance measure is presented to compute the degree of discrimination between IFSs.
ii. A hybrid MCDM method is introduced with the combination of TOPSIS and VIKOR approaches under the context of IFSs.
iii. In this method, the weights of decision makers' (DMs') are calculated through rank sum formula, while the criteria weights are derived via Stepwise Weight Assessment Ratio Analysis (SWARA) model.
iv. To prove the applicability of proposed approach, it is applied to a case study of blockchain network selection problem.

The rest part of this work is presented as: In Section 2, we initially present the basic concepts of IFSs and further develops a new IF-distance measure based on logarithmic function. In Section 3, we develop a hybrid MCDM method for solving MCDM problems under IF environment. In Section 4, we implement the developed method on the evaluation of blockchain networks considering multiple factors. Lastly, Section 5 draws the conclusions and suggests some future research procedures.

2. Proposed Distance Measure for Intuitionistic Fuzzy Sets

This part of study initially presents the background of the work and further proposes a distance measure between the IFSs.

2.1. Preliminaries

This section presents the fundamental definitions related to the proposed approach.

Definition 2.1 [11]. Assume that $T=\{t_1,t_2,...,t_q\}$ be a finite universal set. Atanassov (1986) presented the mathematical definition of an IFS *H* on *T*, which is given as

$$H=\{(t_k,\ \mu_H(t_k),\nu_H(t_k)): t_k\in T\}, \tag{1}$$

where $\mu_H:T\rightarrow[0,1]$ and $\nu_H:T\rightarrow[0,1]$ signify the MG and NMG of an element t_k to *H* in T, such that $0\leq\mu_H(t_k),\nu_H(t_k)\leq 1,\quad \forall\, t_k\in T$. For each $t_k\in T$, the hesitancy degree is defined as $\pi_H(t_k)=1-\mu_H(t_k)-\nu_H(t_k)$. Xu [25] defined this ordered pair "(μ_H,ν_H)" as an 'intuitionistic fuzzy number (IFN)' and can be denoted as $\beta=(\mu,\nu)$.

Definition 2.2 [26]. For an IFN $\beta=(\mu,\nu)$, the score and accuracy values are computed via Eq. (2) and Eq. (3), respectively.

$$Sc(\beta)=0.5(1+\mu-\nu),\ \text{where}\ Sc(\beta)\in[0,1], \tag{2}$$

$$Ac(\beta)=\mu+\nu,\ \text{where}\ Ac(\beta)\in[0,1]. \tag{3}$$

Definition 2.3 [25]. For a collection of IFNs $\beta_k=(\mu_k,\nu_k)(k=1,2,...,q)$, Xu [25] introduced the weighted averaging and geometric operators for IFNs and symbolically denoted as IFWA and IFWG operators, given by Eq. (4) and Eq. (5), respectively.

$$IFWA(\beta_1,\beta_2,...,\beta_q)=\mathop{\oplus}_{k=1}^{q} w_k\,\beta_k=\left[1-\prod_{k=1}^{q}(1-\mu_k)^{w_k},\prod_{k=1}^{q}\nu_k^{w_k}\right], \tag{4}$$

$$IFWG(\beta_1,\beta_2,...,\beta_q)=\mathop{\otimes}_{k=1}^{q}\beta_k^{w_k}=\left[\prod_{k=1}^{q}\mu_k^{w_k},\ 1-\prod_{k=1}^{q}(1-\nu_k)^{w_k}\right]. \tag{5}$$

Definition 2.4 [27]. Let $E,G,H\in IFSs(T)$. A real-valued function $J:IFSs(T)\times IFSs(T)\to[0,1]$ is said to be a distance measure for IFSs if it satisfies the following requirements:

(i) $0\le J(E,G)\le 1,$

(ii) $J(E,G)=0 \Leftrightarrow E=G,$

(iii) $J(E,G)=J(G,E),$

(iv) If $E\subseteq G\subseteq H,$ then $J(E,H)\ge J(E,G)$ and $J(E,H)\ge J(G,H).$

2.2. A Modified Distance Measure between IFSs

Theorem 2.1. For $E,G\in IFSs(T),$ a modified distance measure between IFSs is given in Eq. (6).

$$J(E,G)=\frac{1}{2q\ln 2}\sum_{k=1}^{q}\begin{pmatrix}\left(\mu_E(t_k)-\mu_G(t_k)\right)\times\ln\left(\dfrac{1+\mu_E(t_k)}{1+\mu_G(t_k)}\right)\\ +\left(\nu_E(t_k)-\nu_G(t_k)\right)\times\ln\left(\dfrac{1+\nu_E(t_k)}{1+\nu_G(t_k)}\right)\\ +\left(\pi_E(t_k)-\pi_G(t_k)\right)\times\ln\left(\dfrac{1+\pi_E(t_k)}{1+\pi_G(t_k)}\right)\end{pmatrix}. \tag{6}$$

Proof. To proof this theorem, we need the prove the properties (i)-(iv) of Definition 2.4.

(i) Let us consider that $\left(\mu_E,\nu_E\right)=\left(\mu_G,\nu_G\right).$ Then, Eq. (6) becomes

$$J(E,G)=\frac{1}{2q\ln 2}\sum_{k=1}^{q}\begin{pmatrix}\left(\mu_E(t_k)-\mu_G(t_k)\right)\times\ln\left(\dfrac{1+\mu_E(t_k)}{1+\mu_G(t_k)}\right)\\ +\left(\nu_E(t_k)-\nu_G(t_k)\right)\times\ln\left(\dfrac{1+\nu_E(t_k)}{1+\nu_G(t_k)}\right)\\ +\left(\pi_E(t_k)-\pi_G(t_k)\right)\times\ln\left(\dfrac{1+\pi_E(t_k)}{1+\pi_G(t_k)}\right)\end{pmatrix}=0.$$

Assume that $E=(1,0)$ and $G=(0,1),$ then Eq. (6) becomes

$$J(E,G)=\frac{1}{2\ln 2}\begin{pmatrix}(1-0)\times\ln\left(\dfrac{1+1}{1+0}\right)+(0-1)\times\ln\left(\dfrac{1+0}{1+1}\right)\\ +\left((1-1-0)-(1-0-1)\right)\times\ln\left(\dfrac{1+(1-1-0)}{1+(1-0-1)}\right)\end{pmatrix}=1.$$

Thus, from above discussion, we have $0\le J(E,G)\le 1.$

(ii) Let $J(E,G)=0.$ Then, from Eq. (6), we have

$$J(E,G)=\frac{1}{2q\ln 2}\sum_{k=1}^{q}\begin{pmatrix}\left(\mu_E(t_k)-\mu_G(t_k)\right)\times\ln\left(\dfrac{1+\mu_E(t_k)}{1+\mu_G(t_k)}\right)\\ +\left(\nu_E(t_k)-\nu_G(t_k)\right)\times\ln\left(\dfrac{1+\nu_E(t_k)}{1+\nu_G(t_k)}\right)\\ +\left(\pi_E(t_k)-\pi_G(t_k)\right)\times\ln\left(\dfrac{1+\pi_E(t_k)}{1+\pi_G(t_k)}\right)\end{pmatrix}=0.$$

It implies that

$$\left(\mu_E(t_k)-\mu_G(t_k)\right)\times\ln\left(\frac{1+\mu_E(t_k)}{1+\mu_G(t_k)}\right)=0\quad\Rightarrow\mu_E(t_k)=\mu_G(t_k),\ \forall\ t_k\in T,$$

$$\left(\nu_E(t_k)-\nu_G(t_k)\right)\times\ln\left(\frac{1+\nu_E(t_k)}{1+\nu_G(t_k)}\right)=0 \quad \Rightarrow \nu_E(t_k)=\nu_G(t_k),\ \forall\ t_k\in T,$$

$$\left(\pi_E(t_k)-\pi_G(t_k)\right)\times\ln\left(\frac{1+\pi_E(t_k)}{1+\pi_G(t_k)}\right)=0 \quad \Rightarrow \pi_E(t_k)=\pi_G(t_k),\ \forall\ t_k\in T.$$

Thus, we have $\mu_E(t_k)=\mu_G(t_k),\nu_E(t_k)=\nu_G(t_k)$ and $\pi_E(t_k)=\pi_G(t_k),\ \forall\ t_k\in T.$

Conversely, if $\mu_E(t_k)=\mu_G(t_k),\nu_E(t_k)=\nu_G(t_k)$ and $\pi_E(t_k)=\pi_G(t_k),\ \forall\ t_k\in T,$ then from Eq. (6), it is obvious that $J(E,G)=0.$

(iii) Applying property of logarithmic function on Eq. (6), we get $J(E,G)=J(G,E).$

(iv) Let $E,G,H\in IFSs(T)$ and $E\subseteq G\subseteq H.$ Then, we have $\mu_E(t_k)\leq\mu_G(t_k)\leq\mu_H(t_k),$ $\nu_H(t_k)\leq\nu_G(t_k)\leq\nu_E(t_k)$ and $\pi_E(t_k)\leq\pi_G(t_k)\leq\pi_H(t_k),\ \forall t_k\in T.$ Let us consider a function

$$f(y,\,z)=(y-z)\times\ln\left(\frac{1+y}{1+z}\right). \tag{7}$$

where $0\leq y\leq 1$ and $0\leq z\leq 1.$

Differentiating Eq. (7) partially with respect to *y* and *z*, respectively, we have

$$\frac{\partial f(y,z)}{\partial y}=\left(\ln\left(\frac{1+y}{1+z}\right)+(y-z)\times\left(\frac{1}{1+y}\right)\right), \tag{8}$$

$$\frac{\partial f(y,z)}{\partial z}=-\left(\ln\left(\frac{1+y}{1+z}\right)+(y-z)\times\left(\frac{1}{1+z}\right)\right). \tag{9}$$

When $y\geq z,$ we get $\frac{\partial f(y,z)}{\partial y}\geq 0$ and $\frac{\partial f(y,z)}{\partial z}\leq 0,$ then $f(y,z)$ is increasing with respect to *y* and decreasing with respect to *z*. When $z\geq y,$ we get $\frac{\partial f(y,z)}{\partial y}\leq 0$ and $\frac{\partial f(y,z)}{\partial z}\geq 0,$ then $f(y,z)$ is decreasing with respect to *y* and increasing with respect to *z*. Considering the monotonicity of the function $f(y,z),$ we can have $f\left(\mu_E(t_k),\mu_G(t_k)\right)\leq f\left(\mu_E(t_k),\mu_H(t_k)\right)$ and $f\left(\nu_E(t_k),\nu_G(t_k)\right)\leq f\left(\nu_E(t_k),\nu_H(t_k)\right).$ Also, $f\left(\mu_G(t_k),\mu_H(t_k)\right)\leq f\left(\mu_E(t_k),\mu_H(t_k)\right)$ and $f\left(\nu_G(t_k),\nu_H(t_k)\right)\leq f\left(\nu_E(t_k),\nu_H(t_k)\right).$ Therefore, $J(E,H)\geq J(E,G)$ and $J(E,H)\geq J(G,H).$

3. A Hybrid Intuitionistic Fuzzy MCDM Method

This section combines the benefits the TOPSIS and VIKOR approaches and developed a novel MCDM method, named as TOPKOR, for solving blockchain network selection problem. Here, we present the procedural steps of IF-TOPKOR method along with rank sum formula-based DMs' weights and SWARA-based criteria weight-determining approach.

Step 1: Construct a linguistic decision matrix.

To evaluate the set of alternatives $L=\{l_1,l_2,...,l_p\}$ with respect to attributes/criteria set $U=\{u_1,u_2,...,u_q\},$ a panel $C=\{c_1,c_2,...,c_n\}$ of DMs is created, where each DM presents his/her linguistic opinion regarding the performance of each alternative by means of given evaluation criteria. Thus, we obtain a linguistic decision matrix (LDM) $D=\left(d_{ij}^{(k)}\right),$ $k=1,2,\dots,n$ and further converted into IF-decision matrix (IFDM) using Likert scale.

Step 2: Derive the DMs' weights.

On the basis of DMs' experiences and their skills, a linguistic variable is assigned to each DM and concerted into IFN using given Likert scale. Using Eq. (10), the weight of k^{th} DM is determined, where $k = 1, 2, \dots, n$.

$$\psi_k = \frac{n - r_k + 1}{\sum_{k=1}^{n}(n - r_k + 1)}. \tag{10}$$

Here, 'n' denotes the total number of DMs, r_k signifies the priority rank of each DM and $k = 1, 2, \dots, n$.

Step 3: Aggregate the individuals' decisions.

To determine the mutual performance value of each alternative, we apply the IFWA operator (or IFWG operator) on the IFDM and obtain the Aggregated-IFDM (AIF-DM) $Z = (z_{ij})_{p \times q}$, where

$$z_{ij} = (\mu_{ij}, \nu_{ij}) = IFWA\left(d_{ij}^{(1)}, d_{ij}^{(2)}, \dots, d_{ij}^{(n)}\right) \text{ or } IFWG\left(d_{ij}^{(1)}, d_{ij}^{(2)}, \dots, d_{ij}^{(n)}\right). \tag{11}$$

Step 4: Normalize the AIF-DM.

If the given MCDM problem consisting of benefit and cost categories of criteria, then there is a need to normalize the AIF-DM and obtain the normalized AIF-DM $Z_N = (\bar{z}_{ij})_{p \times q}$, where

$$\bar{z}_{ij} = \begin{cases} z_{ij} = (\mu_{ij}, \nu_{ij}), & \text{for benefit criterion,} \\ z_{ij}^c = (\nu_{ij}, \mu_{ij}), & \text{for cost criterion.} \end{cases} \tag{12}$$

Step 5: Calculate the weights of criteria through IF-SWARA model.

Let $w = \{w_1, w_2, \dots, w_q\}$ be the weights' set of considered criteria, satisfying that $w_1 + w_2 + \dots + w_q = 1$ and $w_j \in [0, 1]$. To derive the criteria weights, we present an integrated weighting procedure using SWARA model under the context of IF-information. In this method, each DM first assigns the linguistic performance value of each criterion. Further, we convert their performance values into intuitionistic fuzzy numbers. The procedural steps of IF-SWARA model are given as follows:

Step 5.1: Aggregate the individual IFNs into an IFN through Eq. (2). After that, find the score value of each aggregated IFN via Eq. (2) and accordingly rank the criteria. Further, rearrange the criteria positions according to their ranks.

Step 5.2: Determine the relative significance rating (s_j) of each attribute. The relative significance rating is obtained from the criterion placed at the second rank, and the succeeding relative significance is determined by comparing the attributes located at j^{th} and $(j-1)^{th}$ positions.

Step 5.3: Evaluate the comparative coefficient (α_j) of j^{th} attribute by Eq. (13), where $j = 1, 2, \dots, q$.

$$\alpha_j = \begin{cases} 1, & j = 1, \\ s_j + 1, & j > 1, \end{cases} \tag{13}$$

where s_j denotes the relative significance rating of j^{th} attribute.

Step 5.4: Determine the initial weight (ρ_j) of j^{th} attribute through Eq. (14), where $j = 1, 2, \dots, q$.

$$\theta_j = \begin{cases} 1, & j = 1, \\ \dfrac{\theta_{j-1}}{\alpha_j}, & j > 1. \end{cases} \tag{14}$$

Step 5.5: With the use of Eq. (15), calculate the subjective weight of j^{th} attribute, where $j = 1, 2, \dots, q$.

$$w = \frac{\theta_j}{\sum_{j=1}^{q} \theta_j}, \; j = 1, 2, ..., q. \tag{15}$$

Step 6: On the basis of obtained criteria weights and IFWA operator, determine the weighted normalized AIF-DM $Z_N^W = \left(\tilde{\tilde{z}}_{ij}\right)_{p \times q}$.

Step 7: Compute the "IF-positive ideal solution (IFPIS)" and "IF-negative ideal solution (PFNIS)" by Eq. (16) and Eq. (17), respectively.

$$\eta_j^+ = \begin{cases} \left(\max\limits_i \mu_{ij}, \min\limits_i \nu_{ij}\right), & \text{for benefit criterion} \\ \left(\min\limits_i \mu_{ij}, \max\limits_i \nu_{ij}\right), & \text{for cost criterion} \end{cases} \quad \text{for } j = 1, 2, ..., q, \tag{16}$$

$$\eta_j^- = \begin{cases} \left(\min\limits_i \mu_{ij}, \max\limits_i \nu_{ij}\right), & \text{for benefit criterion} \\ \left(\max\limits_i \mu_{ij}, \min\limits_i \nu_{ij}\right), & \text{for cost criterion} \end{cases} \quad \text{for } j = 1, 2, ..., q. \tag{17}$$

Step 8: Determine the degree of distance $J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right)$ between an element $\tilde{\tilde{z}}$ and the IFPIS η_j^+.

$$J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right) = \frac{1}{2\, q \ln 2} \sum_{j=1}^{q} w_j \left(\begin{array}{c} \left(\mu_{ij} - \mu_{\eta_j^+}\right) \times \ln\left(\dfrac{1+\mu_{ij}}{1+\mu_{\eta_j^+}}\right) + \left(\nu_{ij} - \nu_{\eta_j^+}\right) \\ \times \ln\left(\dfrac{1+\nu_{ij}}{1+\nu_{\eta_j^+}}\right) + \left(\pi_{ij} - \pi_{\eta_j^+}\right) \times \ln\left(\dfrac{1+\pi_{ij}}{1+\pi_{\eta_j^+}}\right) \end{array} \right). \tag{18}$$

Compute the degree of distance $J\left(\tilde{\tilde{z}}_{ij}, \eta_j^-\right)$ between an element $\tilde{\tilde{z}}$ and the IFNIS η_j^-.

$$J\left(\tilde{\tilde{z}}_{ij}, \eta_j^-\right) = \frac{1}{2\, q \ln 2} \sum_{j=1}^{q} w_j \left(\begin{array}{c} \left(\mu_{ij} - \mu_{\eta_j^-}\right) \times \ln\left(\dfrac{1+\mu_{ij}}{1+\mu_{\eta_j^-}}\right) + \left(\nu_{ij} - \nu_{\eta_j^-}\right) \\ \times \ln\left(\dfrac{1+\nu_{ij}}{1+\nu_{\eta_j^-}}\right) + \left(\pi_{ij} - \pi_{\eta_j^-}\right) \times \ln\left(\dfrac{1+\pi_{ij}}{1+\pi_{\eta_j^-}}\right) \end{array} \right), \tag{19}$$

where w_j represents the j^{th} attribute's weight from Eq. (15).

Step 9: With the use of Eq. (20), compute the maximum distance (F_i) between each alternative and IFPIS, where $i = 1, 2, ..., p.$

$$F_i = \max_j^q J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right), \; i = 1, 2, ..., p. \tag{20}$$

Step 10: Compute the compromise measure/VIKOR index by means of following equation:

$$V_i = \upsilon \left(\frac{J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right) - J^+}{J^+ - J^-} \right) + (1-\upsilon)\left(\frac{F_i - F^+}{F^+ - F^-} \right), \; i = 1, 2, ..., p. \tag{21}$$

Here, $J^+ = \min\limits_i J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right)$, $J^- = \max\limits_i J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right)$, $F^+ = \min\limits_i F_i$, $F^+ = \max\limits_i F_i$ and $\upsilon \in [0,1]$ denotes the relative weight of normalized utility index against normalized regret index [24].

Step 11: Compute the closeness coefficient index of each alternative using Eq. (22).

$$Y_i = \frac{J\left(\tilde{\tilde{z}}_{ij}, \eta_j^-\right)}{J\left(\tilde{\tilde{z}}_{ij}, \eta_j^+\right) + V_i},\ i = 1, 2, ..., p. \tag{22}$$

Prioritize the options along with the descending values of $Y_i, i = 1, 2, ..., p.$ The candidate with the highest closeness coefficient index is the most desirable option.

4. Case Study

Blockchain is an emerging technology that is being implemented in innovative manner by healthcare sector. It is used for health record-keeping, clinical trial, patient monitoring, safety management, display information and transparency [28]. Integrating blockchain network with healthcare is useful to preserve and exchange patient data through hospitals, manage medical and pharmaceutical supply chains, facilitate transactions between healthcare stakeholders, prevent identity fraud and theft [29-30].

This section evaluates the blockchain networks in healthcare based on several conflicting criteria. In this regard, the networks including *Smart Contracts* (l_1), *Data Traceability* (l_2), *Distributed Ledger* (l_3) and *Integration of IoT and Blockchain* (l_4) are considered as potential alternatives for this case study. On the basis of literature survey, online questionnaire and discussion with panel of three experts, we have identified five factors affecting the process of blockchain networks assessment in a particular healthcare center, which are *Data Acquisition, Management and Transparency* (u_1), *Personally Identifiable Information* (u_2), *Lack of regulation* (u_3), *Minimize the energy consumption* (u_4) and *Trust management issues* (u_5) (see Table 1). Here, *Lack of regulation* (u_3) and *Trust management issues* (u_5) are cost type of criteria and others are of benefit types.

Table 1
Details of considered evaluation criteria for blockchain network selection

Factors	Sources
Minimize the energy consumption (u_1)	Pathak et al. [2], Habibullah et al. [31]
Personally Identifiable Information (u_2)	Haleem et al. [29], Saeed et al. [30]
Lack of regulation (u_3)	Jiang et al. [32], Pathak et al. [2]
Data Acquisition, Management and Transparency (u_4)	Haleem et al. [29], Jiang et al. [32], Pathak et al. [2]
Trust management issues (u_5)	Arshad et al. [33], Xiang et al. [34]

4.1. Experimental Results

This subsection implements the proposed TOPKOR approach for solving blockchain network selection problem.

Step 1: Table 2, adopted from Hezam et al. [35], consisting of Likert's scale to evaluate the alternatives, DMs and criteria. With the use of Table 2, each decision maker provides the assessment degrees of blockchain networks considering the evaluation factors and consequently, the LDM is formed in Table 3.

Table 2
Linguistic variables and their corresponding IFNs [35]

LVs	IFNs
Absolute high (AH)	(0.95, 0.05)
Very very high (VVH)	(0.85, 0.10)
Very high (VH)	(0.80, 0.15)
High (H)	(0.70, 0.20)
Moderate good (MH)	(0.60, 0.30)
Medium (M)	(0.50, 0.40)
Moderate low (ML)	(0.40, 0.50)
Low (L)	(0.30, 0.60)
Very low (VL)	(0.20, 0.70)
Very very low (VVL)	(0.10, 0.80)
Absolute low (AL)	(0.05, 0.95)

Table 3
Linguistic decision opinions by the set of three decision makers

	u_1	u_2	u_3	u_4	u_5
l_1	(M, L, ML)	(H, H, MH)	(M, VH, M)	(M, H, VH)	(M, M, L)
l_2	(M, MH, ML)	(MH, H, M)	(M, M, MH)	(ML, ML, H)	(M, H, M)
l_3	(L, H, M)	(MH, H, ML)	(ML, L, VL)	(MH, L, M)	(ML, M, VL)
l_4	(H, VL, M)	(L, M, ML)	(H, L, ML)	(H, MH, L)	(M, L, L)

Step 2: Based on Table 2, we assign the linguistic variable to each DM as per their knowledge and skills. To find the DMs' weights, we transform the assigned linguistic values into IFNs and compute the score values correspondingly. According to obtained score values, we determine the priority rank of each DM and finally compute the numeric weight of each DM using Eq. (10). Table 4 presents the required results.

Table 4
Weights of decision makers

DEs	c_1	c_2	c_3
LRs	H	VVH	VH
Weight	0.1667	0.5	0.3333

Steps 3-4: To merge the individual opinions of DMs, the formula (11) is used for constructing the aggregated intuitionistic fuzzy decision matrix, see Table 5. Since *Lack of regulation* (u_3) and *Trust management issues* (u_5) are cost type of criteria and *Data Acquisition, Management and Transparency* (u_1), *Personally Identifiable Information* (u_2) and *Minimize the energy consumption* (u_4) belongs to benefit category of criteria, then, it is required to create the normalized AIF-DM, see Table 6.

Table 5
Aggregated intuitionistic fuzzy decision matrix

	u_1	u_2	u_3	u_4	u_5
l_1	(0.3713, 0.5277)	(0.6698, 0.2289)	(0.6838, 0.2449)	(0.7146, 0.2040)	(0.4407, 0.4579)
l_2	(0.5248, 0.3732)	(0.6268, 0.2904)	(0.5358, 0.3634)	(0.5238, 0.3684)	(0.6127, 0.2828)
l_3	(0.5904, 0.3026)	(0.6035, 0.2904)	(0.2867, 0.6127)	(0.4300, 0.4670)	(0.3972, 0.5003)
l_4	(0.4192, 0.4714)	(0.4380, 0.4610)	(0.4226, 0.4701)	(0.5406, 0.3533)	(0.3382, 0.5608)

Table 6
Normalized aggregated intuitionistic fuzzy decision matrix

	u_1	u_2	u_3	u_4	u_5
l_1	(0.3713, 0.5277)	(0.6698, 0.2289)	(0.2449, 0.6838)	(0.7146, 0.2040)	(0.4579, 0.4407)
l_2	(0.5248, 0.3732)	(0.6268, 0.2904)	(0.3634, 0.5358)	(0.5238, 0.3684)	(0.2828, 0.6127)
l_3	(0.5904, 0.3026)	(0.6035, 0.2904)	(0.6127, 0.2867)	(0.4300, 0.4670)	(0.5003, 0.3972)
l_4	(0.4192, 0.4714)	(0.4380, 0.4610)	(0.4701, 0.4226)	(0.5406, 0.3533)	(0.5608, 0.3382)

Step 5: To find the criteria weights, we first ask the DMs to provide the linguistic performance value of each criterion during the assessment of blockchain networks. Using Table 2, the DMs' present the linguistic values of criteria in Table 7 and further convert them into IFNs for IF-SWARA model. By means of IFWA operator (4), the aggregated performance value of each criterion is determined. On the basis of their obtained score values, the position of each criterion is arranged. The maximum value of score function determines a criterion with the first position. Next, the ratings of relative importance are calculated from the criterion positioned at the 2nd rank. Further, the comparative coefficients of criteria and their initial weight are derived via Eq. (13) and Eq. (14), respectively. Finally, the weight of each criterion is determined using Eq. (15) and given as $w_j =$ (0.2185, 0.1948, 0.1826, 0.2379, 0.1662). The computational steps of IF-SWARA are given in Table 8.

Table 7
Assessment ratings and score values of criteria

Criteria	c_1	c_2	c_3	Aggregated IFNs	Score values
u_1	ML	MG	M	(0.5390, 0.3595)	0.5898
u_2	M	ML	ML	(0.4180, 0.4817)	0.4681
u_3	L	ML	L	(0.3519, 0.5477)	0.4021
u_4	MG	G	M	(0.6268, 0.2696)	0.6786
u_5	VL	L	ML	(0.3201, 0.5793)	0.3704

Table 8
Computational results by IF-SWARA model

Criteria	Score values	Relative importance	Coefficient degree	Initial weight	Weight
u_4	0.6786	-	1.00	1.000	0.2379
u_1	0.5898	0.0888	1.0888	0.9184	0.2185
u_2	0.4681	0.1217	1.1217	0.8188	0.1948
u_3	0.4021	0.066	1.066	0.7681	0.1826
u_5	0.3704	0.0997	1.0997	0.6985	0.1662

Step 6: Based on the achieved criteria weights and IFWA operator (4), we compute the weighted normalized AIF-DM, given in Table 9.

Table 9
Weighted normalized AIF-DM

	u_1	u_2	u_3	u_4	u_5
l_1	(0.0964, 0.8696)	(0.1941, 0.7503)	(0.0500, 0.9329)	(0.2579, 0.6851)	(0.0968, 0.8727)
l_2	(0.1500, 0.8062)	(0.1747, 0.7859)	(0.0792, 0.8923)	(0.1618, 0.7885)	(0.0537, 0.9218)
l_3	(0.1772, 0.7701)	(0.1649, 0.7859)	(0.1590, 0.7960)	(0.1252, 0.8343)	(0.1089, 0.8577)
l_4	(0.1119, 0.8485)	(0.1062, 0.8600)	(0.1095, 0.8545)	(0.1689, 0.7807)	(0.1278, 0.8351)

Step 7: With the use of Eq. (16) and Eq. (17), the IFPIS and IFNIS are computed and given as follows: $\eta_j^+ =$ {(0.1772, 0.7701), (0.1941, 0.7503), (0.1590, 0.7960), (0.2579, 0.6851), (0.1278,

0.8351)} and $\eta_j^- =$ {(0.0964, 0.8696), (0.1062, 0.8600), (0.0500, 0.9329), (0.1252, 0.8343), (0.0537, 0.9218)}.

Steps 8-11: Using Eqs (18)-(19), we calculate the distances between each alternative and IFPIS, and IFNIS, and shown in Table 10. Utilizing the obtained distances, the maximum distance between alternative and IFPIS is computed based on Eq. (20). Further, the compromise measure of each alternative is determined via Eq. (21) and lastly, the closeness coefficient index of each network option is derived through Eq. (22) and presented in Table 10. On the basis of acquired closeness coefficient index, the ranking order of blockchain networks is $l_4 \succ l_2 \succ l_3 \succ l_1$. Hence, the network "*Integration of IoT and Blockchain* (l_4)" is the best choice among the others with respect to considered evaluation criteria.

Table 10
Computational steps of TOPKOR method for blockchain network selection

	$d\left(\tilde{\tilde{z}}_{ij},\eta_j^+\right)$	$d\left(\tilde{\tilde{z}}_{ij},\eta_j^-\right)$	F_i	V_i	Y_i	Ranking
l_1	0.0047	0.0069	0.0038	0.1351	0.0486	4
l_2	0.0053	0.0024	0.0033	0.4009	0.0060	2
l_3	0.0050	0.0059	0.0065	0.6667	0.0088	3
l_4	0.0056	0.0026	0.0028	0.5000	0.0052	1
Max	0.0056	0.0069	0.0065			
Min	0.0047	0.0024	0.0028			

4.2. Comparative Study

In this part, we compare the results of introduced TOPKOR method with TOPSIS and VIKOR approaches in the context of intuitionistic fuzzy environment.

4.2.1. IF-TOPSIS method

In this subsection, we present the steps of IF-TOPSIS method given by Sun et al. [18] and further implemented it to evaluate the aforesaid blockchain network selection problem.

Step 1: Create the IFDM.

Step 2: Construct the normalized AIF-DM.

Step 3: Compute the IFPIS and IFNIS using the above-discussed Eq. (16) and Eq. (17), respectively.

Step 4: Determine the degree of distances $J\left(\tilde{\tilde{z}}_{ij},\eta_j^+\right)$ and $J\left(\tilde{\tilde{z}}_{ij},\eta_j^-\right)$ between an element $\tilde{\tilde{z}}$ and the IFPIS η_j^+, and the IFNIS η_j^-.

Step 5: Calculate the closeness coefficient index using Eq. (23).

$$B_i = \frac{J\left(\tilde{\tilde{z}}_{ij},\eta_j^-\right)}{J\left(\tilde{\tilde{z}}_{ij},\eta_j^-\right)+J\left(\tilde{\tilde{z}}_{ij},\eta_j^+\right)},\ i=1,2,...,p. \tag{23}$$

Step 6: Arrange the alternatives according to the non-increasing values of closeness coefficient index and choose the optimal one.

Here, we apply the Sun et al.'s [18] IF-TOPSIS method on the aforesaid case study and obtain the positive and negative ideal solutions as same as the proposed approach. Next, the distances $J\left(\tilde{\tilde{z}}_{ij},\eta_j^+\right)$ and $J\left(\tilde{\tilde{z}}_{ij},\eta_j^-\right)$ are similar as the TOPKOR method, given in Table 10. Based on Eq. (23), the closeness coefficient index of each blockchain network is calculated and presented as $B_1 = 0.5948$, $B_2 = 0.3117$, $B_3 = 0.5413$ and $B_4 = 0.3171$. Finally, the ranking order of blockchain networks is $l_1 \succ l_3 \succ l_4 \succ l_2$.

4.2.2. IF-VIKOR method

This section first presents the steps of IF-VIKOR model given by Liang & Liu [23] and further applied to evaluate the aforesaid blockchain network selection problem.

Step 1: Construct the IFDM.

Step 2: Determine the IFPIS and IFNIS.

Step 3: Compute the "group utility (GU)", "individual regret (IR)" and "compromise measure (CM)" of each alternative using Eqs (24)-(26), respectively.

$$G_i = L_{1,i} = \sum_{j=1}^{q} w_j \frac{J\left(\eta_j^+, \tilde{\tilde{z}}_{ij}\right)}{J\left(\eta_j^+, \eta_j^-\right)}, \tag{24}$$

$$R_i = L_{\infty,i} = \max_{1 \le j \le n} \left(w_j \frac{d\left(\eta_j^+, \tilde{\tilde{z}}_{ij}\right)}{d\left(\eta_j^+, \eta_j^-\right)} \right), \tag{25}$$

$$Q_i = \upsilon \frac{\left(G_i - G^+\right)}{\left(G^- - G^+\right)} + \left(1-\upsilon\right) \frac{\left(R_i - R^+\right)}{\left(R^- - R^+\right)}. \tag{26}$$

Step 4: According to the acquired values of *GU*, *IR* and *CM*, rank the alternatives. Minimum value of compromise measure indicates the optimal option.

After applying the Liang & Liu's IF-VIKOR method (Liang & Liu, 2024), the positive and negative ideal solutions are given as $\eta_j^+ =$ {(0.1772, 0.7701), (0.1941, 0.7503), (0.1590, 0.7960), (0.2579, 0.6851), (0.1278, 0.8351)} and $\eta_j^- =$ {(0.0964, 0.8696), (0.1062, 0.8600), (0.0500, 0.9329), (0.1252, 0.8343), (0.0537, 0.9218)}, respectively. Next, using Eqs (24)-(26), the GU, IR and CM of alternatives are computed and given as G_1 = 0.4720, G_2 = 0.5937, G_3 = 0.3447, G_4 = 0.5247, R_1 = 0.2185, R_2 = 0.1684, R_3 = 0.2379, R_4 = 0.1948, Q_1 = 0.6161, Q_2 = 0.5, Q_3 = 0.5 and Q_4 = 0.5514. According to the CM, the ranking order of blockchain networks is $l_1 \succ l_4 \succ l_2 \approx l_3$. Based on the comparative results, we derive the following advantages of the proposed work:

- In this work, we have developed a new distance measure for IFSs, which is based on logarithmic function.
- In this method, the DMs' weights are computed via rank sum model, while existing IF-TOPSIS and IF-VIKOR methods do not consider the weights of DMs.
- For the first time, we have presented the TOPKOR method in the context of IFSs, which does not only derive the rank of blockchain networks but also evaluate the significance values of criteria and decision makers. Moreover, this method takes the combined benefits of TOPSIS and VIKOR methods under the intuitionistic fuzzy environment.

5. Conclusions

In the recent times, BT has been used for developing security innovations in the healthcare sector. It can offer secure data by empowering more reliable trust information and identity authentication. In this work, we have proposed a hybrid MCDM method for assessing and selecting more optimal blockchain network in a healthcare center. In this regard, we have invited a group of three DMs and computed their significance values on the basis of their knowledge and skills. Moreover, we have identified some factors affecting the blockchain network assessment process and determined their weights through IF-SWARA model. Furthermore, the proposed method has been used to rank four blockchain networks on the basis of five factors and found that an option "*Integration of IoT and Blockchain* (l_4)" is the best choice among the others. Lastly, we have compared the results of the proposed approach and with two well-known methods in the context of context of IFSs, which proves its effectiveness over the others. In future, we will try to implement our proposed approach over a large number of data sets. In addition, we can generalize the TOPKOR method under different generalization of fuzzy set, including q-rung orthopair fuzzy rough set, complex q-rung orthopair fuzzy set, interval-valued q-rung orthopair fuzzy soft rough set and Linear diophantine fuzzy set.

Author Contributions

Conceptualization, A. R. M. and P.R.; methodology, P.R.; software, A.R.M.; validation, P.R.; formal analysis, P.R.; investigation, A.R.M.; resources, P.R.; data curation, A.R.M.; writing—original draft preparation, P.R.; writing—review and editing, A.R.M.; visualization, P.R.; supervision, A.R.M.; project administration, P.R. All authors have read and agreed to the published version of the manuscript.

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The data supporting this study are available from the corresponding author upon reasonable request.

Conflicts of Interest

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

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