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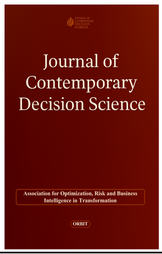

Assessment and Prioritization of Data Analysis Challenges Using Fuzzy Multi-Criteria Decision-Making

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ABSTRACT

Data analysis using different techniques has become increasingly important across a wide range of application domains. However, several challenges arise when datasets are collected, processed, and analysed. This chapter aims to identify and evaluate the most significant challenges associated with data analysis. The proposed methodology is based on multi-criteria decision-making (MCDM). The identified challenges are classified into ten categories: Data Quality Issues, Data Integration, Data Volume, Data Variety, Data Privacy and Security, Bias and Misinterpretation, Skill Gap, Real-Time Analysis, Cost and Infrastructure, and Communicating Results. Two MCDM methods are employed for the numerical evaluation. The data are collected in the form of trapezoidal intuitionistic fuzzy numbers (TrIFNs) to represent the uncertainty and ambiguity inherent in expert assessments. Finally, a comparative analysis is conducted to evaluate the reliability and flexibility of the proposed model.

1. Introduction

For obtaining raw data and subsequently transforming it into useful information, data analysis is a beneficial procedure for use of decision-making. In 1962, the well-known statistician John W. Tukey [1] clearly defined data analysis. It is not usually a single method, but involves multiple methods, each designed to gain specific insights. The four most common types of data analysis are descriptive analysis, diagnostic analysis, predictive analysis and prescriptive analysis. They play a decisive role in transforming raw data into meaningful insights that inform decision-making across several domains. The

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data analysis process is mainly done in six steps. At first, it defines the main problem, then it collects all the data for cleaning. Then, it analyses it for perfect visualization and lastly, interprets the data to make the right decision. In fact, the data is required as input to the analysis and it is specified based on the needs of the analysis customers. Again, the progression of data analysis often involves different challenges that can influence the accuracy, size and reliability of the results. It is essential to identify the most suitable challenges, particularly to improve analytical procedures, enhance data quality and safeguard the effective interpretation. These challenges may include specific concerns and important issues, such as selecting appropriate analytical methods. They are data incompleteness, inconsistency, high dimensionality, noise and confidentiality. Researchers and practitioners can increase the usefulness of data-driven solutions by systematically classifying and addressing these barriers and they can support them with more informative, indication-based results.

1.1 Importance of data analysis

Data analysis is indispensable for transforming large amounts of raw data into various evocative information, as it supports operational decision-making. It helps organizations identify trends, patterns and relationships within data. So, this process can then lead to better tactical planning and problem solving. This data is analyzed primarily to improve the efficiency of businesses. As a result, it can reduce risk and enhance competitive advantage by making informed decisions based on evidence rather than insight. For example, data analysis plays a crucial role in large areas of business. The core function of business operations is the ability to examine, process, and interpret vast amounts of data. Let's take a real-world example of data analytics in business. For example, online shopping and e-commerce companies like Amazon and Flipkart analyze customer data like browsing history, purchase patterns and product ratings. Consuming this analysis, they endorse products to users, optimize pricing and forecast future demand. This supports improvements in sales, customer satisfaction and inventory management. Accurate, well-informed and efficiently implemented data analytics can lead to significant benefits across the entire organizational structure. Through data research, the correct interpretation of the results can be determined by enabling the validity of hypotheses. Overall, it can be said that data analysis upsurges understanding and the power to drive innovation. Moreover, it also plays a vigorous role in ensuring that decisions are data-driven and results-based.

1.2 Motivation of this study

This section briefly explains the motivation for this research work. The motivation behind this study is to categorize and understand the main challenges that affect the reliability, precision and efficiency of data analysis. With the rapid growth of big data from numerous sources, analysts often face problems such as integration difficulties, data quality issues, large data volumes and data variety. Distinguishing these challenges helps refine analytical methods, develop better data management strategies and ensure that data-driven decisions are more informed and trustworthy. This study aims to guide researchers and practitioners in overcoming these obstacles to achieve meaningful and actionable insights. The following points are the motivation for this work, as follows:

(i) Multiple criteria and alternatives are considered to regulate the most effective challenges for data analysis.

(ii) Trapezoidal intuitionistic fuzzy numbers (TrIFN) are taken to seize the ambiguity of the data set. All the data are taken in linguistic terms from three decision makers in an unbiased and transparent way and further converted into TrIFNs.

(iii) De-i-fuzzification method is applied to de-i-fuzzify the fuzzy numbers and utilized in the computational procedure.

(iv) A TrIFN-based MCDM model is constructed, namely the fuzzy Entropy weighted method, which determines the criteria weight and applies it in further evaluation.

(v) Find the most prioritized alternatives with the TrIFN-based decision-making methodology, namely VIKOR.

(vi) Conduct comparative analysis through multiple MCDM methods to examine the consistency and flexibility of the results.

1.3 Research outline

A systematic procedure of collecting, organizing, processing and analyzing data to extract meaningful insights is called data analytics. It is used to identify patterns, trends and relationships in large datasets. In this context, it involves the analysis and interpretation of results using pre-processing methods and statistical or computational techniques used in a research study. This helps make informed decisions and improve the efficiency of solving complex real-world problems. In this study, our goal is to find the most suitable challenges for data analytics through multiple conflicting criteria and alternatives. The ranking of data analytics across different fields depends on various factors and we will select some of these important factors as criteria. Simultaneously, we consider several data analysis processes as alternatives for ranking based on prioritization and usefulness. Then, we will apply two MCDM methods: the entropy weighted method to evaluate the weights of the criteria and the VIKOR method to rank the alternatives. In this framework, trapezoidal intuitionistic fuzzy numbers (TrIFNs) are included to capture and handle the uncertainty in the dataset. Finally, we will conduct a comparative analysis to assess the accuracy, robustness and stability of the results.

1.4 Structure of this chapter

This section describes the structure of this study in detail. The introduction of this research is discussed in Section 1. The literature review of this proposed model is presented in Section 2. Further, the preliminaries of the mathematical tools are discussed in Section 3 and the proposed MCDM methodologies of numerical computation are presented in Section 4. Then, the detailed discussion on the criteria selection process and brief details are conducted in Section 5 and short details of the proposed alternative for adopting the various challenges in data analysis are covered in Section 6, respectively. Furthermore, the model formulation and data collection procedure and the numerical illustration and discussion of the proposed model are presented in Section 7 and Section 8, respectively. After that, the comparative analysis of this study is performed in Section 9 to examine the accuracy of the results. Additionally, the implication of the proposed research is discussed in Section 10. Finally, the conclusion and future research scope of this study are described in Section 11.

2. Literature Survey of this Study

This section discusses the literature studies on the various fields considered for this research. First, we studied the background of data analysis [2], then the mathematical tools [3] and lastly the MCDM methodologies [4] used in recent times, in brief.

2.1 Background on the data analysis

The most appropriate challenges for data analysis [5] can be found in complex datasets to obtain accurate and meaningful results. Data analysts [6] often face various problems, among which missing values, erroneous data, inconsistent formats and large volumes of data are particularly troublesome. Then it becomes difficult to select and apply appropriate analytical techniques when the data is ambiguous and messy. In addition, one of the main problems is identifying the relevant variables that really affect the research results. On the other hand, data obtained in various difficult real-world situations can change over time. For those reasons, its prediction and interpretation become more difficult. However, proper visualization and interpretation of the results are necessary for making the right decisions. There is a need to overcome these challenges and improve the reliability of the data analysis [7] process. Here, Table 1 summarizes recent studies on data analysis.

Table 1
Some recent studies on data analysis with associated information

Author	Year	Application Area
[8] Brown, A. W. et. al.	2007	Potential solutions to data and analytics problems for the continuous improvement of scientific practice
[5] Wongsuphasawat, K. et. al.	2019	Exploratory data analysis through research based on interviews with 18 data analysts
[9] Stieglitz, S. et. al.	2018	Identify and analyze the challenges of topic discovery, data collection, and data preparation in the social media analytics process
[10] Fan, J. et. al.	2014	Discusses the statistical and computational methods of the main characteristics of big data by providing new perspectives and describes the impact of paradigm shifts in computing architecture
[2] Efron, B. et. al.	2018	Description of the main methods for determining the accuracy and efficiency of algorithms used to automate statistical decisions in the computer age
[11] Twisk, J. W. R. et. al.	2013	Applied longitudinal data analysis for epidemiology
[6] Svergun, D. I.	1991	Application of modern mathematical methods to the problem of processing and interpreting small-angle diffraction data analysis
[12] Konold, C. et. al.	2022	Data analysis as a search for signals in noisy processes
[7] Aitchison, J. et. al.	2005	Constructive data analysis about our current state and our path forward
[13] Hoaglin , D. C. et. al.	2000	Robust and exploratory data analysis

2.2 Background of the mathematical tool

Generally, fuzzy sets [3] can handle uncertainty in the data set and the model. Unlike classical sets, any element of a fuzzy set can belong to a set with a membership value between 0 and 1. Fuzzy sets are widely used in real-life control systems, decision making, pattern recognition and artificial intelligence. Moreover, mathematically, it is applied in various studies such as optimization, differential equations and difference equations.

We apply trapezoidal intuitionistic fuzzy numbers (TrIFN) to obtain an accurate representation of this research work in uncertain environments throughout the MCDM process. Through it, it is possible to work in a larger fuzzy environment. It is possible to effectively express uncertainty by demonstrating the ability to make decisions for various reasons in different contexts. TrIFN is mainly an extension of intuitionistic fuzzy numbers (IFN) [14] and trapezoidal fuzzy numbers (TrFN) [15]. Some of its necessary applications in real life are, for example, the use of airport efficiency from the perspective of passengers [15], the application of IFN in neural networks [16] and the application in energy production time inspection using sustainable life cycles in Industry 4.0 [17]. Again, different studies that have applied TrFN are described below, such as the application in the analysis of an advanced fuzzy time series forecasting method [18], the application in the selection of a sustainable restaurant location along the highway [19], the discovery of a new fuzzy MCDM method based on trapezoidal fuzzy AHP and hierarchical fuzzy integrals [20], the application of a trapezoidal fuzzy number-based method for ranking decision alternatives by group choice and aggregation in decision making [21] and many more. Further, Mandal, S. et al. [22] applied interval-valued Pythagorean trapezoidal fuzzy numbers in the diagnosis of psychiatric disorder using MCDM methods.

We use TrIFN to address the data analysis model problem in this study. Here, some articles on TrIFN are described they are, such as the use in ranking method [23], to find optimized path in a network [24], a new ranking method and application in MCDM [25] and in an automobile company through MCDM methods [26] and so on. Further, Aslam, M. U. et al. [27] applied TrIFNs to define monitoring of health ranges and Meher, B. B. et al. [28] utilized TrIFNs to determine the site selection of Photovoltaic using MCGDM methods. Additionally, Meher, B. B. et al. [29] select a wind power plant site selection using an aggregating operator with the WASPAS method under TrIFNs environments. After that, Huang, H. et al. [30] applied a fuzzy tensor-based method to supplier selection in TrIFNs environments.

2.3 *Literature of the MCDM methodologies*

Multi-criteria decision making (MCDM) [22] is a specialized branch of operations research that deals with decision-making problems involving multiple and conflicting criteria. They are used to evaluate the weights of the criteria [19] proposed in the model and to determine their order. It includes various methods, techniques and approaches that assign importance to the criteria. Moreover, different alternatives can be evaluated, compared and prioritized to make the best possible decision. Decision-making methods consider both quantitative and qualitative factors during the decision-making process. They are widely applied to solve problems related to business, engineering, resource management, medical diagnostics and location selection. There are various MCDM methods to solve these complex problems, such as Entropy [31], AHP [31], TOPSIS [32], CRITIC [33], COPRAS [34], WASPAS [35], MULTIMOORA [35], VIKOR [36], DEMATEL [37], etc. In this paper, we will use the Entropy [38] and the VIKOR [39] methods to solve the model.

An objective weighting technique is the Entropy method [40], which is widely used to weight criteria based on data variability in MCDM problems. It measures the amount of uncertainty present in the information for each criterion obtained from the model. Again, a criterion with more variability among the alternatives is given a higher weight because it provides more useful information. The method is not subjective, but rather relies on mathematical calculations. The entropy method is commonly applied to problems related to engineering, economics, management science and data analysis. Several of its applications are discussed below, such as the medical field [41], the selection of suitable locations for wind power plants [38], financial optimization [42] and the analysis of failure modes in water treatment plants [31].

VIKOR [43] is a popular MCDM technique used to rank and select alternatives based on multiple conflicting criteria. This method usually focuses on identifying a compromise solution. In this case, the obtained solution is closest to the ideal solution but furthest from the negative-ideal solution. It can introduce a multi-criteria ranking index based on measures of group utility and individual regret. It is widely applied to problems in engineering design, supplier selection and environmental management, as well as to balancing decision-makers' highest collective satisfaction and lowest individual dissatisfaction. In practice, the VIKOR method has various applications, such as identifying a suitable site for a nuclear power plant in Indonesia [44], the selection process of batteries used in vehicles [4], developing a modified VIKOR model for multi-criteria decision-making from the perspective of regret theory [45], water quality assessment [39] and so on.

3. Preliminaries of Mathematical Tools

In this section, we will get an introduction to fuzzy sets, fuzzy numbers, and their extensions. In mathematics, fuzzy sets are often used to deal with ambiguity, vagueness and uncertain situations in real-world problems. In this case, membership functions are used in fuzzy sets [46] to represent partial truth values instead of just the exact binary values 0 or 1. They are widely applied in decision-making, engineering, medical diagnosis, artificial intelligence and optimization problems to solve complex real-world scenarios.

3.1 Fuzzy sets and fuzzy numbers

Fuzzy sets were invented in 1965 by Lotfi A. Zadeh [3] to model various types of uncertain and vague data. In this study, we consider a mathematical tool that handles uncertain data by allowing partial membership rather than a definite yes or no value. In mathematical modelling, it is used to represent uncertain numerical values, usually as an extension of set theory, specifically crisp set theory. The basic definitions and properties of fuzzy sets are described below:

Definition 1. ***Fuzzy set:*** *[46]*

Assume that $(\mathscr{H})$ be the universal set of discourse. A fuzzy set $\tilde{\mathscr{W}}$ is defined on it. Therefore, $\tilde{\mathscr{W}}$ can be inscribed as

$$\tilde{\mathscr{W}} = \{(\tau, \mu_{\tilde{\mathscr{W}}}(\tau)) : \tau \in \mathscr{H}\} \tag{1}$$

where, $\mu_{\tilde{\mathscr{W}}} : \mathscr{H} \to [0,1]$ be the membership function of the element τ, where $(\tau \in \mathscr{H})$.

Example 1. *Consider the air conditioner in a room is cooling it. Then, the reference set of temperature conditions in a room is $\mathscr{I} = \{i_1, i_2, i_3, i_4, i_5\}$. Here, "Cool" is using the fuzzy term. So, consider $\tilde{\mathscr{C}}$ to be the fuzzy set of "Cool" temperatures. Then, the set is,*

$$\tilde{\mathscr{C}} = \{(i_1, 0.2), (i_2, 0.4), (i_3, 0.6), (i_4, 0.8), (i_5, 1.0)\}$$

where, the temperature condition i_1 is "Cool" of range 0.2 and so forth.

Definition 2. ***Fuzzy number:*** *[46]*

The following five conditions must be expressed for a fuzzy set $\tilde{\mathscr{W}}$ over the set of real numbers $\mathbb{R}$, s.t.,

- *Let $\tilde{\mathscr{W}}$ be a normal fuzzy set, that is, $f \in \tilde{\mathscr{W}}$ must contain an element such that, $\mu_{\tilde{\mathscr{W}}}(f) = 1$.*
- *${}^{\alpha}\tilde{\mathscr{W}} = \{f : \mu_{\tilde{\mathscr{W}}}(f) \geq \alpha\}$ need to be a closed interval for every $\alpha \in (0,1]$.*
- *$\tilde{\mathscr{W}}$ should be a support limited to a certain range.*
- *The membership function of $\tilde{\mathscr{W}}$ need to be piecewise continuous.*
- *${}^{\alpha}\tilde{\mathscr{W}}$ be the convex fuzzy set, where, $\mu_{\tilde{\mathscr{W}}}(\vartheta f_1 + (1-\vartheta) f_2) \geq \min\{\mu_{\tilde{\mathscr{W}}}(f_1), \mu_{\tilde{\mathscr{W}}}(f_2)\} \, \forall \, f_1, f_2 \in \tilde{\mathscr{W}}$ and $\vartheta \in [0,1]$.*

Example 2. *Air conditioners are a classic real-life example of fuzzy logic. Because "slightly warm" can correspond to a partial cooling level like 24-26°C. The controller then adjusts the speed of the compressor gradually, without suddenly turning it on or off, to provide smooth and comfortable temperature control. Assumed that the air conditioner in the room is cooling it. So, the word "Cool" can not express the exact temperature and the term "Cool" can vary from person to person. So, we can use the concept of a fuzzy number by selecting this as an object. Then, from 0 ("Not Cool" in fuzzy idea) to 1 ("Cool" in fuzzy idea) is the membership function of the mentioned object.*

Remark 1. *A fuzzy number is a fuzzy set that always fulfills, see in Definition 2. It is defined on the set of real numbers* $(\mathbb{R})$*. It can be said that, although all fuzzy numbers are fuzzy sets, the converse is not always true. Again, each element of the fuzzy set has a unique membership value to describe the element's inclusion in the set. Various fuzzy numbers can be expressed by triangular, trapezoidal, pentagonal, hexagonal, bell-shaped membership functions, etc.*

3.2 Intuitionistic fuzzy set and its extension

Atanosov, K. et al. [14] invented the intuitionistic fuzzy set (IFS) in 1989. An IFS is presented by an ordered triplet consisting of an element, its membership and non-membership degree. It is essentially an extension of fuzzy set, which can consider both membership and non-membership dimensions under uncertainty. In complex uncertainty situations, it is used to represent an unknown quantity. In this section, we will discuss about the intuitionistic fuzzy sets (IFS), trapezoidal fuzzy numbers (TrFNs) and trapezoidal intuitionistic fuzzy numbers (TrIFNs) in detail.

Definition 3. ***Intuitionistic fuzzy set (IFS):*** *[47]*

Choose that, an Intuitionistic Fuzzy Set (IFS) $(\tilde{\mathfrak{P}})$ *defined on a universal set* $\mathscr{H}$*. Then, the IFS* $(\tilde{\mathfrak{P}})$ *is denoted as*

$$\tilde{\mathfrak{P}} = \left\{\left(\zeta; \mu_{\tilde{\mathfrak{P}}}(\zeta), \nu_{\tilde{\mathfrak{P}}}(\zeta)\right) : \zeta \in \mathscr{H}\right\} \tag{2}$$

where, the membership and non-membership functions of $(\tilde{\mathfrak{P}})$ *are* $\mu_{\tilde{\mathfrak{P}}}(\zeta)$ *and* $\nu_{\tilde{\mathfrak{P}}}(\zeta)$*, respectively, i.e.,* $\mu_{\tilde{\mathfrak{P}}}(\zeta), \nu_{\tilde{\mathfrak{P}}}(\zeta) : \mathscr{H} \to [0,1] \forall\, \zeta \in \mathscr{H}$*. And,* $0 \leq \mu_{\tilde{\mathfrak{P}}}(\zeta) + \mu_{\tilde{\mathfrak{P}}}(\zeta) \leq 1$ *for any* $\zeta \in \mathscr{H}$*.*

Example 3. *Let, an IFS* $(\tilde{\mathscr{Q}})$ *is defined on the universal set* $\mathscr{H}$*. Then,* $\tilde{\mathscr{Q}}$ *is indicated as,* $\tilde{\mathscr{Q}} = (0.6, 0.2)$ *instead of* $\tilde{\mathscr{Q}} = \{(z; 0.6, 0.2) : z \in \mathscr{H}\}$*, where* 0.6 *and* 0.2 *be the membership and non-membership functions, respectively, with the condition* $0 \leq 0.6 + 0.2 \leq 1$ *for any* $z \in \mathscr{H}$*.*

Definition 4. ***Trapezoidal fuzzy number (TrFN):*** *[48]*

Let, $\kappa_1, \kappa_2, \kappa_3, \kappa_4$ *be the real numbers and* $\tilde{\mathscr{B}} = \{\langle s, (\kappa_1, \kappa_2, \kappa_3, \kappa_4); \rangle\, \mu_{\tilde{\mathscr{B}}}(s) : s \in \mathbb{R}\}$ *be a Trapezoidal Fuzzy Number (TrFN) whose membership function* $\mu_{\tilde{\mathscr{B}}}(s)$ *define as,*

$$\mu_{\tilde{\mathscr{B}}}(s) = \begin{cases} \frac{s-\kappa_1}{\kappa_2-\kappa_1} & ;\text{ when } \kappa_1 \leq s < \kappa_2 \\ 1 & ;\text{ when } \kappa_2 \leq s \leq \kappa_3 \\ \frac{\kappa_4-s}{\kappa_4-\kappa_3} & ;\text{ when } \kappa_3 < s \leq \kappa_4 \\ 0 & ;\text{ otherwise} \end{cases} \tag{3}$$

where $\kappa_1 \leq \kappa_2 \leq \kappa_3 \leq \kappa_4$*.*

Example 4. *Assume* $\tilde{\mathscr{A}} = \{\langle s, (1,2,3,4)\rangle\, \mu_{\tilde{\mathscr{A}}}(s) : s \in \mathbb{R}\}$ *be a TrFN define on the set of real numbers* $(\mathbb{R})$ *with its membership function define as*

$$\mu_{\tilde{\mathscr{A}}}(s) = \begin{cases} \frac{s-1}{2-1} & ;\text{ when } 1 \leq s < 2 \\ 1 & ;\text{ when } 2 \leq s \leq 3 \\ \frac{4-s}{4-3} & ;\text{ when } 3 < s \leq 4 \\ 0 & ;\text{ otherwise} \end{cases} \tag{4}$$

The membership function $(\mu_{\tilde{\mathscr{A}}}(s))$ of TrFN $\tilde{\mathscr{A}}$ define in Example 4 is trapezoidal in shape when $s \in [1,4]$. The graphical representation of the trapezoidal fuzzy number (TrFN) and its membership functions in Figure 1.

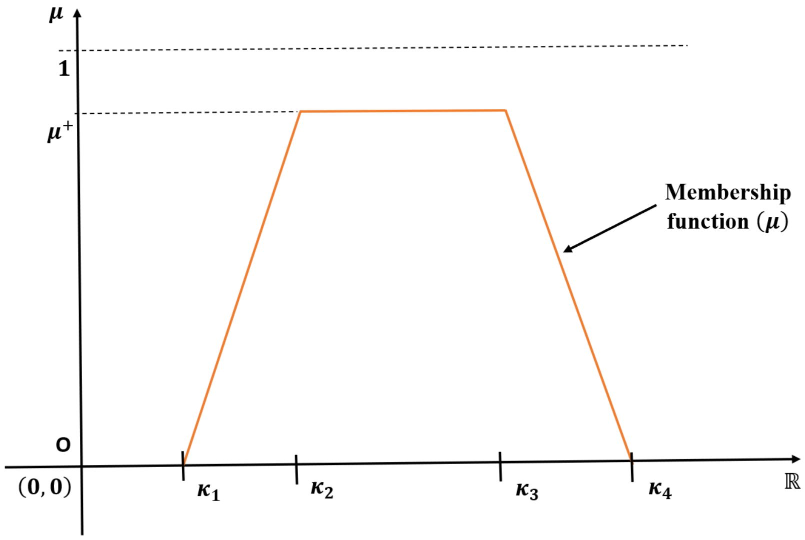

Fig. 1. Graphical structure of the trapezoidal fuzzy number (TrFN)

Definition 5. ***Trapezoidal intuitionistic fuzzy number (TrIFN):*** *[49]*

Let, a trapezoidal intuitionistic fuzzy number (TrIFN) $\tilde{\mathcal{M}} = \{\langle a, (\gamma_1, \gamma_2, \gamma_3, \gamma_4)\rangle\, \mu_{\tilde{\mathcal{M}}}(a), \nu_{\tilde{\mathcal{M}}}(a) : a \in \mathbb{R}\}$ *is defined on* $\mathbb{R}$ *with the base of membership* $(\mu_{\tilde{\mathcal{M}}}(a))$ *and non-membership* $(\nu_{\tilde{\mathcal{M}}}(a))$ *functions which are presented by*

$$\mu_{\tilde{\mathcal{M}}}(a) = \begin{cases} \frac{a-\gamma_1}{\gamma_2-\gamma_1} & ;\text{ when } \gamma_1 \leq a < \gamma_2 \\ 1 & ;\text{ when } \gamma_2 \leq a \leq \gamma_3 \\ \frac{\gamma_4-a}{\gamma_4-\gamma_3} & ;\text{ when } \gamma_3 < a \leq \gamma_4 \\ 0 & ;\text{ otherwise} \end{cases} \tag{5}$$

and

$$\nu_{\tilde{\mathcal{M}}}(a) = \begin{cases} \frac{\gamma_2-a}{\gamma_2-\gamma_1} & ;\text{ when } \gamma_1 \leq a < \gamma_2 \\ 0 & ;\text{ when } \gamma_2 \leq a \leq \gamma_3 \\ \frac{a-\gamma_3}{\gamma_4-\gamma_3} & ;\text{ when } \gamma_3 < a \leq \gamma_4 \\ 1 & ;\text{ otherwise} \end{cases} \tag{6}$$

where $\gamma_1 \leq \gamma_2 \leq \gamma_3 \leq \gamma_4$ *and* $0 \leq \mu_{\tilde{\mathcal{M}}}(a) + \nu_{\tilde{\mathcal{M}}}(a) \leq 1, \forall a \in \mathbb{R}$.

Example 5. *Let us consider,* $\tilde{\mathcal{X}} = \{(2, 4, 6, 8); 0.6, 0.2\}$ *instead of* $\tilde{\mathcal{X}} = \{\langle r, (2, 4, 6, 8); 0.6, 0.2\rangle : r \in \mathbb{R}\}$ *be a trapezoidal intuitionistic fuzzy number (TrIFN), where,* $2 < 4 < 6 < 8$, $0 \leq 0.6 + 0.2 \leq 1$ *and for any* $r \in \mathbb{R}$. *So, the membership function* $(\mu_{\tilde{\mathcal{X}}})$ *and the non-membership function* $(\nu_{\tilde{\mathcal{X}}})$ *is denoted as,*

$$\mu_{\tilde{\mathcal{X}}} = \begin{cases} \frac{r-2}{2} & ;\text{ when } 2 \leq r < 4 \\ 1 & ;\text{ when } 4 \leq r \leq 6 \\ \frac{8-r}{2} & ;\text{ when } 6 < r \leq 8 \\ 0 & ;\text{ otherwise} \end{cases}$$

and

$$\nu_{\tilde{\mathcal{X}}} = \begin{cases} \frac{2-a}{2} & ;\text{ when } 2 \leq a < 4 \\ 0 & ;\text{ when } 4 \leq a \leq 6 \\ \frac{a-6}{2} & ;\text{ when } 6 < a \leq 8 \\ 1 & ;\text{ otherwise} \end{cases}$$

Definition 6. ***Generalized trapezoidal intuitionistic fuzzy number (GTrIFN):*** *[49]*

Let, a generalized trapezoidal intuitionistic fuzzy number (GTrIFN) $\tilde{\mathcal{N}} = \{\langle a, (\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu^+, \nu^- \rangle \mu_{\tilde{\mathcal{N}}}(a), \nu_{\tilde{\mathcal{N}}}(a) : a \in \mathbb{R}\}$ is defined on $\mathbb{R}$ with the base of membership $(\mu_{\tilde{\mathcal{N}}}(a))$ and non-membership $(\nu_{\tilde{\mathcal{N}}}(a))$ functions which are presented by

$$\mu_{\tilde{\mathcal{N}}}(a) = \begin{cases} \mu^+ \frac{a-\gamma_1}{\gamma_2-\gamma_1} & ;\text{ when } \gamma_1 \leq a < \gamma_2 \\ \mu^+ & ;\text{ when } \gamma_2 \leq a \leq \gamma_3 \\ \mu^+ \frac{\gamma_4-a}{\gamma_4-\gamma_3} & ;\text{ when } \gamma_3 < a \leq \gamma_4 \\ 0 & ;\text{ otherwise} \end{cases} \tag{7}$$

and

$$\nu_{\tilde{\mathcal{N}}}(a) = \begin{cases} \nu^- + (1-\nu^-)\frac{\gamma_2-a}{\gamma_2-\gamma_1} & ;\text{ when } \gamma_1 \leq a < \gamma_2 \\ \nu^- & ;\text{ when } \gamma_2 \leq a \leq \gamma_3 \\ \nu^- + (1-\nu^-)\frac{a-\gamma_3}{\gamma_4-\gamma_3} & ;\text{ when } \gamma_3 < a \leq \gamma_4 \\ 1 & ;\text{ otherwise} \end{cases} \tag{8}$$

where μ^+ and ν^- are the optimal value of the membership and non-membership functions and $\gamma_1 \leq \gamma_2 \leq \gamma_3 \leq \gamma_4$ and $0 \leq \mu_{\tilde{\mathcal{N}}}(a) + \nu_{\tilde{\mathcal{N}}}(a) \leq 1, \forall a \in \mathbb{R}$.

Remark 2. *In the further computation process, we consider the generalized trapezoidal intuitionistic fuzzy number (GTrIFN) as a trapezoidal intuitionistic fuzzy number (TrIFN). The membership and non-membership functions are not always optimal (i.e., $\mu^+ \leq 1$ and $0 \leq \nu^-$).*

Remark 3. *A TrIFN is an extension of the trapezoidal fuzzy number (TFN) that takes into account the membership and non-membership functions. This number offers huge flexibility with accuracy compared to traditional fuzzy numbers for its hesitation degrees. So, the hesitation degree of the above TrIFN $\tilde{\mathcal{N}}$ is, $\pi_{\tilde{\mathcal{N}}}(a) = 1 - \mu_{\tilde{\mathcal{N}}}(a) - \nu_{\tilde{\mathcal{N}}}(a)$. The TrIFN is very crucial for presenting imprecise information in real-life multi-criteria decision-making (MCDM), engineering, optimization and management sciences.*

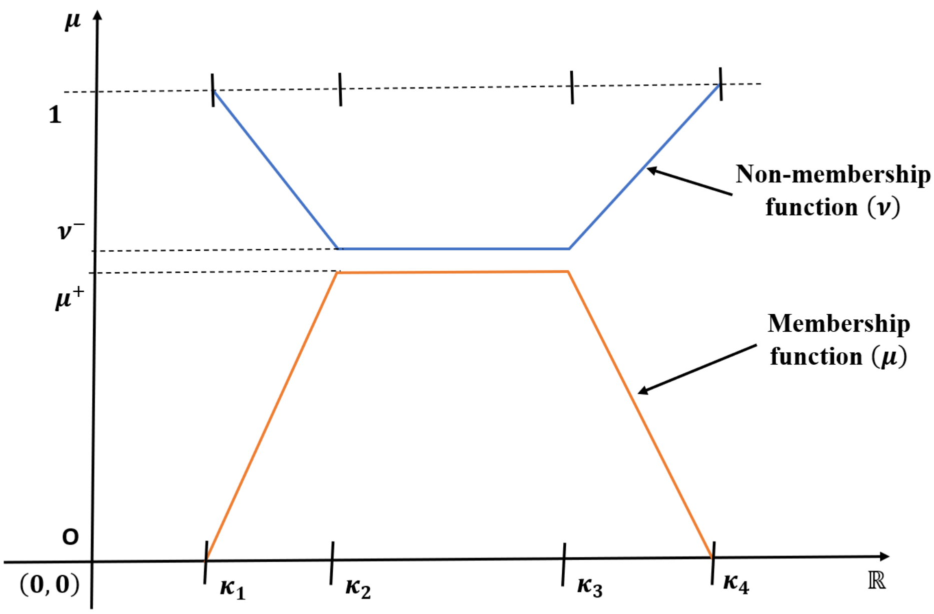

Fig. 2. Structural view of the trapezoidal intuitionistic fuzzy number (TrIFN)

The graphical representation of TrIFN and its membership and non-membership functions are shown in Figure 2. The membership and non-membership functions are in trapezoidal in shape.

The range of membership function $(\mu_{\tilde{N}}(a))$ and non-membership function $(\nu_{\tilde{N}}(a))$ are always $[0,1]$ and satisfies the condition $0 \leq \mu_{\tilde{N}}(a) + \mu_{\tilde{N}}(a) \leq 1$ for all $a \in \mathbb{R}$. The uncertainty capturing capacity of the TrIFNs is geometrically presented in Figure 3. It shows the interrelation between the membership and non-membership functions and their boundaries.

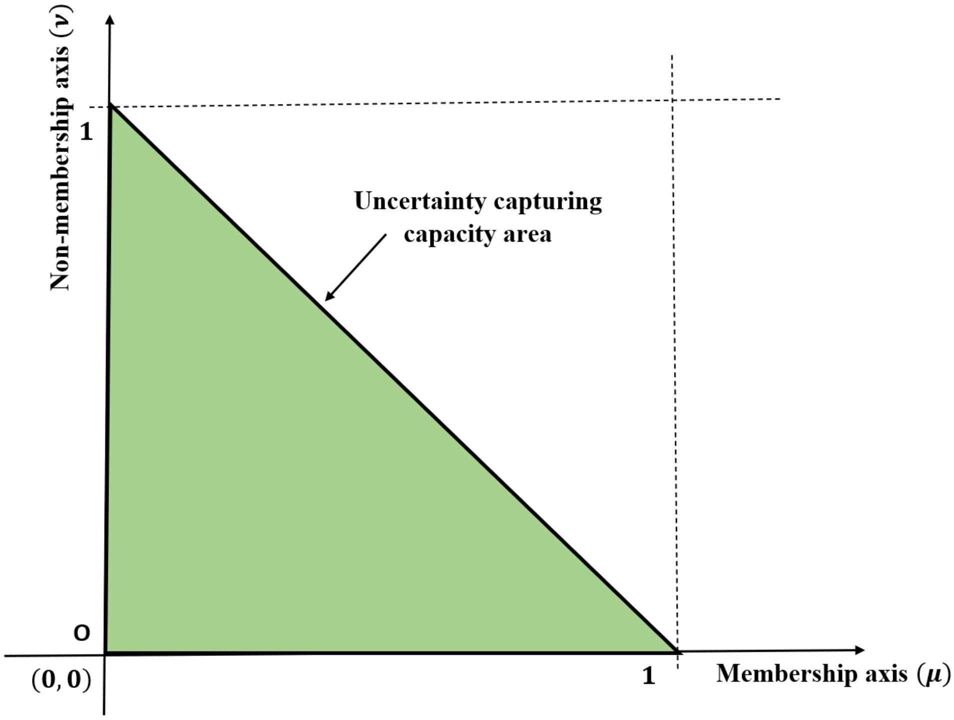

Fig. 3. Comparison between membership function and non-membership function of TrIFN

3.3 *Properties of trapezoidal intuitionistic fuzzy numbers (TrIFNs)*

Consider, $\tilde{\mathcal{M}} = \{(\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\}$ and $\tilde{\aleph} = \{(\ell_1, \ell_2, \ell_3, \ell_4)\,; \mu_{\tilde{\aleph}}, \nu_{\tilde{\aleph}}\}$ be two TrIFNs define on the real number $\mathbb{R}$ in the place of $\tilde{\mathcal{M}} = \{\langle a, (\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}(a), \nu_{\tilde{\mathcal{M}}}(a)\rangle : a \in \mathbb{R}\}$ and $\tilde{\aleph} = \{\langle e, (\ell_1, \ell_2, \ell_3, \ell_4); \mu_{\tilde{\aleph}}(e), \nu_{\tilde{\aleph}}(e)\rangle : e \in \mathbb{R}\}$, respectively. Furthermore, let, α is the positive real number $(\alpha \in \mathbb{R}^+)$. Then, the arithmetic operations on TrIFNs $\tilde{\mathcal{M}}$ and $\tilde{\aleph}$ are described as,

(a) **Addition of two TrIFNs:**
The addition of these two TrIFNs $\tilde{\mathcal{M}}$ and $\tilde{\aleph}$ is define as

$$\begin{aligned}\tilde{\mathcal{M}} \oplus \tilde{\aleph} &= \{(\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\} \oplus \{(\ell_1, \ell_2, \ell_3, \ell_4)\,; \mu_{\tilde{\aleph}}), \nu_{\tilde{\aleph}}\} \\ &= \left\{\left(\gamma_1 + \ell_1, \gamma_2 + \ell_2, \gamma_3 + \ell_3, \gamma_4 + \ell_4; \min\left(\mu_{\tilde{\mathcal{M}}},\, \mu_{\tilde{\aleph}}\right), \max\left(\nu_{\tilde{\mathcal{M}}},\, \nu_{\tilde{\aleph}}\right)\right)\right\}\end{aligned} \tag{9}$$

(b) **Subtraction of two TrIFNs:**
The subtraction of these two TrFNs $\tilde{\mathcal{M}}$ and $\tilde{\aleph}$ is define as

$$\begin{aligned}\tilde{\mathcal{M}} \ominus \tilde{\aleph} &= \{(\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\} \ominus \{(\ell_1, \ell_2, \ell_3, \ell_4)\,; \mu_{\tilde{\aleph}}), \nu_{\tilde{\aleph}}\} \\ &= \left\{\left(\gamma_1 - \ell_4, \gamma_2 - \ell_3, \gamma_3 - \ell_2, \gamma_4 - \ell_1; \min\left(\mu_{\tilde{\mathcal{M}}},\, \mu_{\tilde{\aleph}}\right), \max\left(\nu_{\tilde{\mathcal{M}}},\, \nu_{\tilde{\aleph}}\right)\right)\right\}\end{aligned} \tag{10}$$

(c) **Multiplication of TrIFN:**

$$\begin{aligned}\tilde{\mathcal{M}} \otimes \tilde{\aleph} &= \{(\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\} \otimes \{(\ell_1, \ell_2, \ell_3, \ell_4)\,; \mu_{\tilde{\aleph}}), \nu_{\tilde{\aleph}}\} \\ &= \left\{\left(\gamma_1\ell_1, \gamma_2\ell_2, \gamma_3\ell_3, \gamma_4\ell_4; \max\left(\mu_{\tilde{\mathcal{M}}},\, \mu_{\tilde{\aleph}}\right), \min\left(\nu_{\tilde{\mathcal{M}}},\, \nu_{\tilde{\aleph}}\right)\right)\right\}\end{aligned} \tag{11}$$

where $\gamma_1 > 0$ and $\ell_1 > 0$.

(d) **Scalar Multiplication of TrIFN:**

$$\begin{aligned}\alpha\tilde{\mathcal{M}} =& \alpha \times \tilde{\mathcal{M}} = \alpha \times \{(\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\} \\ &= \begin{cases} \{(\alpha\gamma_1, \alpha\gamma_2, \alpha\gamma_3, \alpha\gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\} & \text{; when } \aleph \geq 0, \\ \{(\alpha\gamma_4, \alpha\gamma_3, \alpha\gamma_2, \alpha\gamma_1); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\} & \text{; when } \aleph < 0 \end{cases}\end{aligned} \tag{12}$$

Example 6. *Consider,* $\tilde{\mathcal{X}} = \{(2, 3, 4, 5); 0.6, 0.2\}$ *and* $\tilde{\mathcal{Y}} = \{(6, 7, 8, 9); 0.5, 0.4\}$ *are two TrIFNs define on the real number* $\mathbb{R}$*. Furthermore, assume that,* 4 *be a scalar number* $(4 \in \mathbb{R}^+)$*. Then, the arithmetic operations on TrIFNs* $\tilde{\mathcal{X}}$ *and* $\tilde{\mathcal{Y}}$ *are described as*

(a) Addition of two TrIFNs $\tilde{\mathcal{X}}$ *and* $\tilde{\mathcal{Y}}$ *is,*

$$\begin{aligned}\tilde{\mathcal{X}} \oplus \tilde{\mathcal{Y}} &= \{(2, 3, 4, 5); 0.6, 0.2\} \oplus \{(6, 7, 8, 9); 0.5, 0.4\} \\ &= \{(8, 10, 12, 14)\,; 0.5, 0.4\}\end{aligned}$$

(b) Subtraction of two TrIFNs $\tilde{\mathcal{X}}$ *and* $\tilde{\mathcal{Y}}$ *is,*

$$\begin{aligned}\tilde{\mathcal{X}} \ominus \tilde{\mathcal{Y}} &= \{(2, 3, 4, 5); 0.6, 0.2\} \ominus \{(6, 7, 8, 9); 0.5, 0.4\} \\ &= \{(-7, -5, -3, -1)\,; 0.5, 0.4\}\end{aligned}$$

(c) Multiplication of two TrIFNs $\tilde{\mathcal{X}}$ *and* $\tilde{\mathcal{Y}}$ *is,*

$$\begin{aligned}\tilde{\mathcal{X}} \otimes \tilde{\mathcal{Y}} &= \{(2, 3, 4, 5); 0.6, 0.2\} \otimes \{(6, 7, 8, 9); 0.5, 0.4\} \\ &= \{(12, 21, 32, 45)\,; 0.6, 0.2\}\end{aligned}$$

(d) Scalar multiplication of TrIFN $\tilde{\mathcal{X}}$ *is,*

$$\begin{aligned}4 \times \tilde{\mathcal{X}} =& 4 \times \{(2, 3, 4, 5); 0.6, 0.2\} \\ &= \{(8, 12, 16, 20); 0.6, 0.2\}\end{aligned}$$

3.4 De-i-fuzzification method of TrIFN

This section discusses the de-fuzzification method [50] of the TrIFN. Since there is no order relation in the fuzzy set, then there is no comparison among the fuzzy numbers. To overcome these problems, there are several processes considered, such as the de-fuzzification method, de-i-fuzzification method, score function, accuracy function, various operators and others.

De-i-fuzzification [51] is the process of converting an intuitionistic fuzzy valued number convert into a single crisp numerical value, where as the order relations exist. In the application of real-world problems, like decision-making, de-i-fuzzification methodology is crucial. Some of the common de-i-fuzzification methods proposed in various studies include the centre of gravity (COG) method, mean of maximum (MOM) method, bisector method (BM), largest of minimum (LOM) method, smallest of maximum (SOM) method and others. Multiple de-i-fuzzification methods have already been introduced in various research articles for TrIFN, depending on the nature of the problem. In this study, we consider the de-i-fuzzification method under intuitionistic fuzzy fields as follows:

Definition 7. *Let us consider* $\tilde{\mathcal{M}} = \{(\gamma_1, \gamma_2, \gamma_3, \gamma_4); \mu_{\tilde{\mathcal{M}}}, \nu_{\tilde{\mathcal{M}}}\}$ *be a TrIFN define on the set of real numbers* $(\mathbb{R})$. *The de-i-fuzzification method on the TrIFN is denoted by* $\mathcal{S}\left(\tilde{\mathcal{M}}\right)$ *and evaluated as*

$$\mathcal{S}\left(\tilde{\mathcal{M}}\right) = \frac{(\gamma_1 + 2\gamma_2 + 2\gamma_3 + \gamma_4)}{6}\left(\mu_{\tilde{\mathcal{M}}} - \nu_{\tilde{\mathcal{M}}}\right) \tag{13}$$

where $\mu_{\tilde{\mathcal{M}}}$ *and* $\nu_{\tilde{\mathcal{M}}}$ *are the membership and non-membership value of the TrIFN* $\tilde{\mathcal{M}}$, *respectively.*

Remark 4. *In the case of fuzzy systems, de-i-fuzzification is the process of converting fuzzy values into a single crisp value. In this paper, de-i-fuzzification, as described in Equation (13), measures the overall value of TrIFN based on the balance of membership and non-membership values. It makes fuzzy information suitable for decision-making by comparing it with real data. As a result, it provides clear real number, bridging the gap between fuzzy logic and real-world applications.*

Example 7. *Assume* $\tilde{\mathcal{N}} = \{(2, 4, 6, 8)\,; 0.8, 0.2\}$ *be a TrIFN define on the set of real numbers* $(\mathbb{R})$. *Then, the de-i-fuzzification value of* $\tilde{\mathcal{N}}$ *is* $\left(\mathcal{S}(\tilde{\mathcal{N}})\right)$ *and determine as*

$$\begin{aligned}\mathcal{S}\left(\tilde{\mathcal{N}}\right) &= \frac{(2 + 2 \times 4 + 2 \times 6 + 8)}{6}\,(0.8 - 0.2) \\ &= \frac{30}{6}(0.6)\ = 3\end{aligned}$$

4. Proposed MCDM Methodologies

This section discusses the mathematical process of two multi-criteria decision-making (MCDM) methods [34] in the trapezoidal intuitionistic fuzzy number (TrIFN) environment [24]. Decision-making methods are widely used to evaluate the importance of associated factors and make selections in complex scenarios involving multiple conflicting criteria, sub-criteria, alternatives and decision makers (DMs). Several popular MCDM methods are utlized in various studies, including AHP [52], Entropy [40], CRITIC, MEREC, TOPSIS [52], COPRAS, PROMETHEE, WASPAS, CoCoSo [53], MABAC, VIKOR [40] and many more. The entropy method [38] is generally used to determine the weight of the criteria based on the degree of diversity of data and the amount of information. In this case, higher diversity in the values of the criteria indicates greater importance; therefore, their weights are also higher. On the other hand, the effective compromise-ranking method VIKOR [42], which identifies the best solution closest to the ideal alternative by considering the measure of personal regret. Therefore, the combined Entropy VIKOR method [40] helps the model framework to make an accurate, reliable and precise decision for real optimization problems.

4.1 *Entropy weighted method*

The entropy weighted method (EWM) is a widely used MCDM-based weighted calculation methodology that was introduced by Shannon, C. E. [54] in 1948. This method [4] can handle several criteria, alternatives, and decision experts simultaneously and usually does not rely on individual expert opinions. In EWM, indicators with high data variability should be given higher weights because they contain more useful information. Conversely, some indicators with low variability, because they contain less useful information, are assigned lower weights. A graphical flowchart of the entropy-weighted method in a fuzzy environment is depicted in Figure 4.

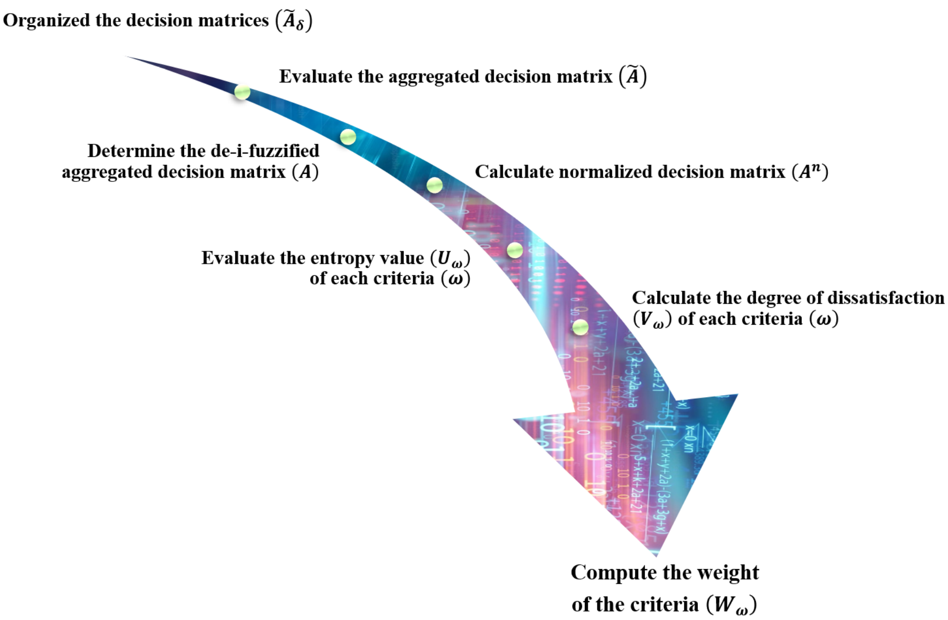

Fig. 4. Structural flowchart of the entropy weighted method

In this study, we consider Ω criteria and Σ alternatives associated with this model. It is also assumed that there are Δ decision makers (DMs) provide significant opinions based on their real-world experience and knowledge, thus moving one step closer to solving the model's problem. The entropy method consists of the following steps:

A. Organized the decision matrices $\left(\tilde{\mathcal{A}}_\delta\right)$:

The decision matrices $(\tilde{\mathcal{A}}_\delta)$ formulated by the δth decision makers (DMs) based on their experience, knowledge and given on the ωth criteria based on σth alternatives in linguistic terms. Furthermore, the decision matrices are converted into TrIFNs using a conversion table. Then the decision matrices $(\tilde{\mathcal{A}}_\delta)$ are in $\Sigma \times \Omega$ order formed as

$$\tilde{\mathcal{A}}_\delta = \left[\left(\tilde{\mathcal{E}}_{\sigma\omega}\right)_\delta\right]_{\Sigma\times\Omega} = \begin{bmatrix} \left(\tilde{\mathcal{E}}_{11}\right)_\delta & \left(\tilde{\mathcal{E}}_{12}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{1\omega}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{1\Omega}\right)_\delta \\ \left(\tilde{\mathcal{E}}_{21}\right)_\delta & \left(\tilde{\mathcal{E}}_{22}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{2\omega}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{2\Omega}\right)_\delta \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \left(\tilde{\mathcal{E}}_{\sigma 1}\right)_\delta & \left(\tilde{\mathcal{E}}_{\sigma 2}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{\sigma\omega}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{\sigma\Omega}\right)_\delta \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \left(\tilde{\mathcal{E}}_{\Sigma 1}\right)_\delta & \left(\tilde{\mathcal{E}}_{\Sigma 2}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{\Sigma\omega}\right)_\delta & \cdots & \left(\tilde{\mathcal{E}}_{\Sigma\Omega}\right)_\delta \end{bmatrix}_{\Sigma\times\Omega} \tag{14}$$

where $\delta = 1, 2. \ldots, \Delta$. Additionally, the $\sigma\omega$th entry of the decision matrices $(\tilde{\mathcal{A}}_\delta)$ is a TrIFN and represents as

$$\begin{aligned} \left(\tilde{\mathcal{E}}_{\sigma\omega}\right)_\delta &= (\{(\chi_1, \chi_2, \chi_3, \chi_4); \mu_{\tilde{\mathcal{E}}}, \nu_{\tilde{\mathcal{E}}}\}_{\sigma\omega})_\delta \\ &= \left(\left\{(\chi_1, \chi_2, \chi_3, \chi_4)_{\sigma\omega}; \mu_{\tilde{\mathcal{E}}_{\sigma\omega}}, \nu_{\tilde{\mathcal{E}}_{\sigma\omega}}\right\}\right)_\delta \\ &= \left(\left\{((\chi_1)_{\sigma\omega}, (\chi_2)_{\sigma\omega}, (\chi_3)_{\sigma\omega}, (\chi_4)_{\sigma\omega})\, ; \mu_{\tilde{\mathcal{E}}_{\sigma\omega}}, \nu_{\tilde{\mathcal{E}}_{\sigma\omega}}\right\}\right)_\delta \\ &= \left\{(((\chi_1)_{\sigma\omega})_\delta\, , ((\chi_2)_{\sigma\omega})_\delta\, , ((\chi_3)_{\sigma\omega})_\delta\, , ((\chi_4)_{\sigma\omega})_\delta)\, ; \left(\mu_{\tilde{\mathcal{E}}_{\sigma\omega}}\right)_\delta , \left(\nu_{\tilde{\mathcal{E}}_{\sigma\omega}}\right)_\delta\right\} \end{aligned} \tag{15}$$

where $\omega = 1, 2, \ldots, \Omega$ and $\sigma = 1, 2, \ldots, \Sigma$, respectively.

B. Evaluate the aggregated decision matrix $\left(\tilde{\mathcal{A}}\right)$:

The Δ number of decision matrices $(\tilde{\mathcal{A}}_\delta)$ are transformed into a single aggregated decision matrix $(\tilde{\mathcal{A}})$ by aggregating each and every entry of it. The aggregated decision matrix $(\tilde{\mathcal{A}})$ is constructed as

$$\tilde{\mathcal{A}} = \left[\tilde{\mathcal{E}}_{\sigma\omega}\right]_{\Sigma\times\Omega} = \begin{bmatrix} \tilde{\mathcal{E}}_{11} & \tilde{\mathcal{E}}_{12} & \cdots & \tilde{\mathcal{E}}_{1\omega} & \cdots & \tilde{\mathcal{E}}_{1\Omega} \\ \tilde{\mathcal{E}}_{21} & \tilde{\mathcal{E}}_{22} & \cdots & \tilde{\mathcal{E}}_{2\omega} & \cdots & \tilde{\mathcal{E}}_{2\Omega} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\mathcal{E}}_{\sigma 1} & \tilde{\mathcal{E}}_{\sigma 2} & \cdots & \tilde{\mathcal{E}}_{\sigma\omega} & \cdots & \tilde{\mathcal{E}}_{\sigma\Omega} \\ \vdots & \vdots & \ddots & \vdots & \ddots & \vdots \\ \tilde{\mathcal{E}}_{\Sigma 1} & \tilde{\mathcal{E}}_{\Sigma 2} & \cdots & \tilde{\mathcal{E}}_{\Sigma\omega} & \cdots & \tilde{\mathcal{E}}_{\Sigma\Omega} \end{bmatrix}_{\Sigma\times\Omega} \tag{16}$$

where $\omega = 1, 2, \ldots, \Omega$ and $\sigma = 1, 2, \ldots, \Sigma$. The $\sigma\omega$th entry $\tilde{\mathcal{E}}_{\sigma\omega}$ of the aggregated decision matrix $(\tilde{\mathcal{A}})$ is evaluated as

$$\begin{aligned} \tilde{\mathcal{E}}_{\sigma\omega} &= \{(\chi_1, \chi_2, \chi_3, \chi_4); \mu_{\tilde{\mathcal{E}}}, \nu_{\tilde{\mathcal{E}}}\}_{\sigma\omega} \\ &= \left\{ \left(\frac{\sum_{\delta=1}^{\Delta} ((\chi_1)_{\sigma\omega})_\delta}{\Delta}, \frac{\sum_{\delta=1}^{\Delta} ((\chi_2)_{\sigma\omega})_\delta}{\Delta}, \frac{\sum_{\delta=1}^{\Delta} ((\chi_3)_{\sigma\omega})_\delta}{\Delta}, \frac{\sum_{\delta=1}^{\Delta} ((\chi_4)_{\sigma\omega})_\delta}{\Delta} \right); \right. \\ &\qquad \left. \min_{\delta=1,2,\ldots,\Delta} \left\{ \left(\mu_{\tilde{\mathcal{E}}_{\sigma\omega}}\right)_\delta \right\}, \max_{\delta=1,2,\ldots,\Delta} \left\{ \left(\nu_{\tilde{\mathcal{E}}_{\sigma\omega}}\right)_\delta \right\} \right\} \end{aligned} \tag{17}$$

where $\delta = 1, 2, \ldots, \Delta$.

C. Determine the de-i-fuzzified aggregated decision matrix $(\mathcal{A})$:

The aggregated decision matrix $(\tilde{\mathcal{A}})$ is transformed into the de-i-fuzzified aggregated decision matrix $(\mathcal{A})$ by de-i-fuzzifying each entry using Equation (13) of the modified decision matrix. The de-i-fuzzified aggregated decision matrix $(\mathcal{A})$ formed as

$$\mathcal{A} = [\mathcal{E}_{\sigma\omega}]_{\Sigma\times\Omega} = \left[\mathcal{S}\left(\tilde{\mathcal{E}}_{\sigma\omega}\right)\right]_{\Sigma\times\Omega} \tag{18}$$

where $\mathcal{E}_{\sigma\omega}$ be the de-i-fuzzified value of $\sigma\omega$th entry with $\omega = 1, 2, \ldots, \Omega$ and $\sigma = 1, 2, \ldots, \Sigma$.

D. Calculate normalized decision matrix $(\mathcal{A}^n)$:

The normalized de-i-fuzzified aggregated decision matrix $(\mathcal{A}^n)$ is evaluated from the de-i-fuzzified aggregated decision matrix $(\mathcal{A})$ by normalizing every entry of it. The normalized decision matrix $(\mathcal{A}^n)$ determined as follows:

$$\mathcal{A}^n = [\mathcal{E}^n_{\sigma\omega}]_{\Sigma\times\Omega} = \left[\frac{\mathcal{E}_{\sigma\omega}}{\sum_{\sigma=1}^{\Sigma} \mathcal{E}_{\sigma\omega}}\right]_{\Sigma\times\Omega} \tag{19}$$

where $\omega = 1, 2, \ldots, \Omega$ and $\sigma = 1, 2, \ldots, \Sigma$.

E. Evaluate the entropy value $(\mathcal{U}_\omega)$ of each criteria (ω):

The entropy value $(\mathcal{U}_\omega)$ of each criteria (ω) is calculated from the normalized decision matrix $(\mathcal{A}^n)$ as

$$\mathcal{U}_\omega = -\frac{1}{\log\Omega} \times \sum_{\sigma=1}^{\Sigma} \left[\mathcal{E}^n_{\sigma\omega} \times \log\left(\mathcal{E}^n_{\sigma\omega}\right)\right] \tag{20}$$

where $\mathcal{E}^{n}_{\sigma\omega}$ be the $\sigma\omega$th entry of normalized decision matrix $(\mathcal{A}^{n})$, Ω be the number of criteria and $\omega = 1, 2, \ldots, \Omega$.

F. Calculate the degree of dissatisfaction $(\mathcal{V}_{\omega})$ of each criteria (ω):
From the entropy value $(\mathcal{U}_{\omega})$ of each criteria (ω), we determine the degree of dissatisfaction $(\mathcal{V}_{\omega})$ using Equation (21), as follows:

$$\mathcal{V}_{\omega} = 1 - \mathcal{U}_{\omega} \tag{21}$$

where $\omega = 1, 2, \ldots, \Omega$.

G. Compute the weight of the criteria $(\mathcal{W}_{\omega})$:
Finally, the weight of the criteria $(\mathcal{W}_{\omega})$ is evaluate using Equation (22), as

$$\mathcal{W}_{\omega} = \frac{\mathcal{V}_{\omega}}{\sum_{\omega=1}^{\Omega} \mathcal{V}_{\omega}} \tag{22}$$

where $\mathcal{V}_{\omega}$ be the degree of dissatisfaction of the criteria ω and $\omega = 1, 2, \ldots, \Omega$.

The weight of the criteria $(\mathcal{W}_{\omega})$ calculated by the entropy weighted method is defined in Equation (22) and further utilized in the ranking-based optimization method to prioritized alternatives.

4.2 VIKOR ranking methodology

The Višekriterijumska Optimizacija I Kompromisno Resenje (VIKOR) methodology was developed by Serafim Opricovic and Gwo-Hshiung Tzeng [43] in 2004. It is an MCDM technique that is used to evaluate and rank multiple alternatives based on conflicting criteria. Its [55] primary goal is to find a compromise solution that maximizes group utility while minimizing individual regret. The method ranks each alternative based on its relative distance from the best and worst values of each criterion in the model. The procedure of the VIKOR method under a fuzzy environment is graphically presented in Figure 5.

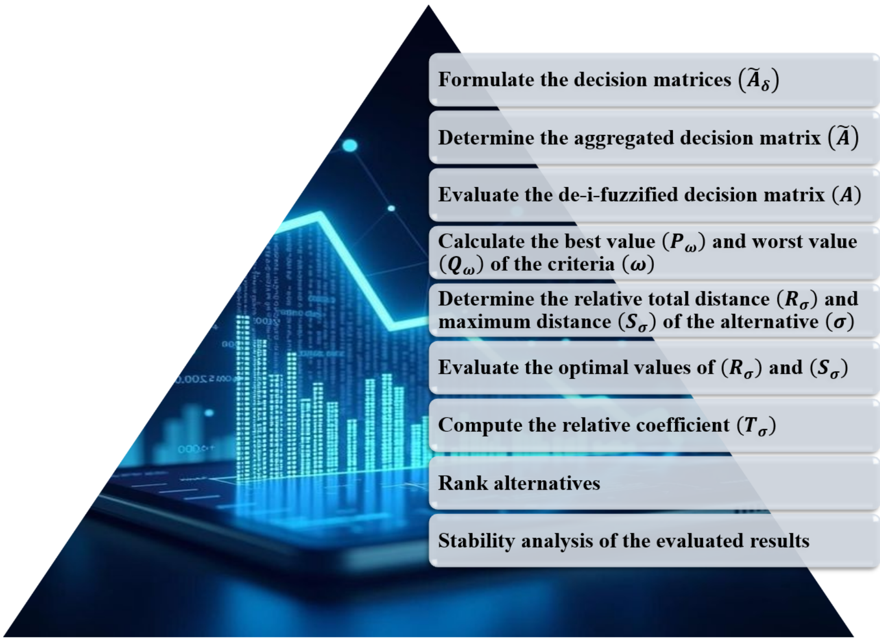

Fig. 5. Flowchart of the VIKOR methodology

In this study, we assume that there are Ω number of criteria, Σ number of alternatives and Δ number of decision makers (DMs) involved in the numerical computations. The DMs are given their opinions in the decision matrix format. The VIKOR method in a fuzzy environment is processed in the following steps:

1. **Formulate the decision matrices $\left(\tilde{\mathcal{A}}_\delta\right)$:**
   The decision matrices $(\tilde{\mathcal{A}}_\delta)$ structured by the δth DMs are shown in Step A of the entropy weighted method (EWM). The decision matrices $(\tilde{\mathcal{A}}_\delta)$ are represents in Equation (14) by TrIFNs whose $\sigma\omega$th entry structured as Equation (15), respectively.

2. **Determine the aggregated decision matrix $\left(\tilde{\mathcal{A}}\right)$:**
   All Δ numbers of decision matrices $(\tilde{\mathcal{A}}_\delta)$ are merged into single decision matrix $(\tilde{\mathcal{A}})$ in Step B of the EWM. The decision matrix $(\tilde{\mathcal{A}})$ is formulated in Equation (16) with the help of the aggregating operator discussed in Equation (17).

3. **Evaluate the de-i-fuzzified decision matrix $(\mathcal{A})$:**
   The de-i-fuzzified decision matrix $(\mathcal{A})$ calculated from the aggregated decision matrix $(\tilde{\mathcal{A}})$ using the de-i-fuzzification formula described in Equation (13) and represented in Equation (18) (i.e., in Step C. of the EWM).

4. **Calculate the best value $(\mathcal{P}_\omega)$ and worst value $(\mathcal{Q}_\omega)$ of the criteria (ω):**
   The best value $(\mathcal{P}_\omega)$ of the the criteria (ω) is determined by Equation (23), as follows:

$$\mathcal{P}_\omega = \begin{cases} \max\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{E}_{\sigma\omega}\} & \text{; if } \omega \text{ be beneficial criteria} \\ \min\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{E}_{\sigma\omega}\} & \text{; if } \omega \text{ be non-beneficial criteria} \end{cases} \tag{23}$$

   and the worst value $(\mathcal{Q}_\omega)$ of the the criteria (ω) is evaluated by Equation (24), as follows:

$$\mathcal{Q}_\omega = \begin{cases} \min\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{E}_{\sigma\omega}\} & \text{; if } \omega \text{ be beneficial criteria} \\ \max\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{E}_{\sigma\omega}\} & \text{; if } \omega \text{ be non-beneficial criteria} \end{cases} \tag{24}$$

   where $\mathcal{E}_{\sigma\omega}$ be the $\sigma\omega$th entry of the de-i-fuzzified decision matrix $(\mathcal{A})$ and $\omega = 1, 2, \ldots, \Omega$.

5. **Determine the relative total distance $(\mathcal{R}_\sigma)$ and maximum distance $(\mathcal{S}_\sigma)$ of the alternative (σ):**
   Calculate the relative total distance $(\mathcal{R}_\sigma)$ of the alternative σ using Equation (25), as follows:

$$\mathcal{R}_\sigma = \sum_{\omega=1}^{\Omega} \left[\mathcal{W}_\omega \times \frac{\mathcal{P}_\omega - \mathcal{E}_{\sigma\omega}}{\mathcal{P}_\omega - \mathcal{Q}_\omega} \right] \tag{25}$$

   and evaluate the relative maximum distance $(\mathcal{S}_\sigma)$ of the alternative σ using Equation (26), as follows:

$$\mathcal{S}_\sigma = \max_{\omega=1,2,\ldots,\Omega} \left\{ \mathcal{W}_\omega \times \frac{\mathcal{P}_\omega - \mathcal{E}_{\sigma\omega}}{\mathcal{P}_\omega - \mathcal{Q}_\omega} \right\} \tag{26}$$

   where $\mathcal{E}_{\sigma\omega}$ be the the $\sigma\omega$th entry of the de-i-fuzzified decision matrix $(\mathcal{A})$, $\mathcal{P}_\omega$ be the best value and $\mathcal{Q}_\omega$ be the worst value of the criteria ω and $\mathcal{W}_\omega$ be the weight of the criteria ω evaluated in Equation (22), respectively with $\sigma = 1, 2, \ldots, \Sigma$.

6. **Evaluate the optimal values of $(\mathcal{R}_\sigma)$ and $(\mathcal{S}_\sigma)$:**
   Determine the optimal value of the relative total distance $(\mathcal{R}_\sigma)$ using Equation (27), as

$$\begin{cases} \mathcal{R}^+ = \max\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{R}_\sigma\} \\ \mathcal{R}^- = \min\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{R}_\sigma\} \end{cases} \tag{27}$$

   and calculate the optimal value of the relative maximum distance $(\mathcal{S}_\sigma)$ using Equation (28), as

$$\begin{cases} \mathcal{S}^+ = \max\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{S}_\sigma\} \\ \mathcal{S}^- = \min\limits_{\sigma=1,2,\ldots,\Sigma} \{\mathcal{S}_\sigma\} \end{cases} \tag{28}$$

   where $\sigma = 1, 2, \ldots, \Sigma$.

7. **Compute the relative coefficient $(\mathcal{T}_\sigma)$:**
   Finally, evaluate the relative coefficient $(\mathcal{T}_\sigma)$ value of the alternative σ, using Equation (29), as follows:

$$\mathcal{T}_\sigma = \lambda \times \frac{\mathcal{R}_\sigma - \mathcal{R}^-}{\mathcal{R}^+ - \mathcal{R}^-} + (1-\lambda) \times \frac{\mathcal{S}_\sigma - \mathcal{S}^-}{\mathcal{S}^+ - \mathcal{S}^-} \tag{29}$$

   where λ is the weight of the majority of criteria or the maximum group utility value and in this study, we consider $\lambda = 0.5$ with $\sigma = 1, 2, \ldots, \Sigma$.

8. **Rank alternatives:**
   The alternatives are prioritized based on the relative coefficient $(\mathcal{T}_\sigma)$ values determined in Equation (29). The alternatives are ranked in ascending order, that is, the less relative coefficient $(\mathcal{T}_\sigma)$ value is the best alternative compared with the high relative coefficient $(\mathcal{T}_\sigma)$ value of the alternative (σ) with $\sigma = 1, 2, \ldots, \Sigma$.

9. **Stability analysis of the evaluated results:**
   Proposed first alternative $\mathcal{D}^1$ (ranked as 1) as a compromise solution on the basis of the ranking by $(\mathcal{T}^1)$ (minimum value among $\sigma = 1, 2, \ldots, \Sigma$) successively holds

   a. Acceptable average:

$$\mathcal{T}(\mathcal{D}^2) - \mathcal{T}(\mathcal{D}^1) \leq \mathcal{U} = \frac{1}{1-\Sigma} \tag{30}$$

      Similarly, $\mathcal{T}(\mathcal{D}^2)$ shows the relative coefficient value of the second ranked alternative $(\mathcal{D}^2)$ and Σ is the number of alternatives.

   b. Acceptable stability in decision making:
      Based on $\mathcal{R}_\sigma$ or/and $\mathcal{S}_\sigma$ values alternative $\mathcal{D}^1$ raked as optimal rank. Then they conclude that the compromise solution is stable with subject to

      i. maximum group unity (when $\lambda > 0.5$ is needed),
      ii. or by consensus $\lambda \approx 0.5$,
      iii. or with veto $(\lambda < 0.5)$,

      as λ mentioned in Step 7. If the above conditions are not satisfied, the other compromised solutions are hypotheses as follows:

      * alternatives $\mathcal{D}^1$ and $\mathcal{D}^2$ are compromised solutions when condition b. is unsatisfied, or

* alternatives $\mathcal{D}^1, \mathcal{D}^2, \ldots, \mathcal{D}^{\Sigma'}$ are the compromised solutions when condition a. unsatisfied.

If $\mathcal{T}(\mathcal{D}^2) - \mathcal{T}(\mathcal{D}^1) \geq \mathcal{U} = \frac{1}{1-\Sigma}$ is determined to evaluate the $\mathcal{D}^{\Sigma'}$ value for maximum Σ' (the location of these alternatives are 'in closeness').

5. Criteria Selection for Evaluating the Challenges for Data Analysis

In the field of data analytics, criteria such as data quality issues, data integration, data volume, data diversity, data privacy and security, bias and misinterpretation, lack of expertise, real-time analysis, cost and infrastructure, and reporting of results are very important in data analytics. Because they directly affect the accuracy and usefulness of analytical results. On the one hand, high-quality and well-organized data ensures accurate insights, while data diversity management can effectively manage complex datasets. Confidentiality, skilled professionalism, real-time analysis capabilities and adequate infrastructure enable effective processing of data. Proper implementation of these ensures that informed business and institutional decisions can be made through the insights obtained. The relevant importance criteria for data analysis are considered through detailed literature reviews and consultation with decision experts. The criteria related to the analysis of various challenges of data are depicted in Figure 6. Additionally, a short discussion of the criteria is presented below:

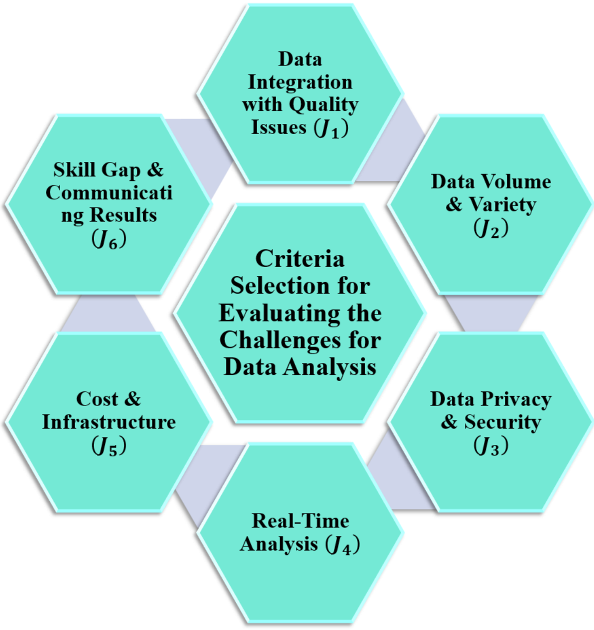

Fig. 6. Related criteria for evaluating the challenges for data analysis

5.1 *Data Integration with Quality Issues* (J_1)

In the case of Big Data, data integration is billed as a major challenge, along with data quality issues. It is mainly the process of combining different data sources as well as maintaining inherent errors, such as data errors, duplicates, or format mismatches. This can happen because data is often collected from multiple sources. Such inconsistent data reduces the reliability of the integrated dataset. As a result, the data quality can be low and misleading analysis can lead to loss of business decisions [8]. Moreover, missing values, different naming conventions, and conflicting record integration further complicate the process. To ensure data consistency and accuracy, thorough profiling, cleaning, and validation are required. Therefore, organizations need to establish governance policies. The problem should be resolved by identifying and automatically checking the data quality using advanced integration tools. Therefore, it can be said that successful data integration largely depends on the continuous monitoring and management of data quality throughout the data life cycle.

5.2 Data Volume & Variety (J_2)

The volume and variety of data actually define the scope and diversity of information. This poses significant challenges for data analysis [9] due to the large volume of data generated across various sources. The huge amount of data generated from various sources typically ranges from terabytes to petabytes. This is essential for extracting effective business insights and running machine learning models effectively. Organizations mainly collect structured (rows of traditional SQL databases), semi-structured (JSON or XML files) and unstructured data (emails, audio, video files and social media posts, etc.) from various databases, social media, sensors, websites and mobile devices. To properly manage and store this huge amount of data, a scalable infrastructure is required, including distributed computing frameworks (e.g. Apache Spark, Hadoop) and advanced technologies such as scalable cloud storage. The integration, processing and analysis of different data formats further complicate the issue by providing a 360-degree view for customers. As a result, analysts must use different strategies to organize data for meaningful insights, as traditional data management tools struggle to handle the diversity of modern datasets. Big Data platforms help to efficiently process and analyze large and diverse datasets through tools to extract, transform, and load (ETL) data into a centralized repository. Therefore, effectively managing the volume and diversity of data is essential for accurate, timely data analysis.

5.3 Data Privacy & Security (J_3)

When dealing with large amounts of sensitive data, data privacy and security become paramount. Generally, users protect the privacy of their data by controlling how their personal information is collected, used and shared with their consent. Furthermore, encrypting that data maintains its security. Therefore, it is necessary for data analysis [2] to adopt legal measures, such as data protection laws, to ensure data privacy. Security measures such as data access control and authentication further protect data. Weak security measures can lead to reputational damage, financial losses and legal penalties. Overall, regular monitoring, testing and risk assessment become essential to maintain a secure data environment with strong privacy and security measures.

5.4 Real-Time Analysis (J_4)

Real-time data analytics [56] is the process of collecting data as it enters a system, processing it and analyzing it appropriately. Real-time OLAP databases help organizations gain immediate insights and take timely decisions by working in milliseconds to seconds. The constant flow of data from various sources, such as sensors, social media, financial transactions and IoT devices, poses significant challenges for its processing. Real-time data analytics becomes important as it processes a continuous live stream, unlike traditional batch-processing methods. Therefore, low-latency processing, high-speed data ingestion (via streaming platforms) and efficient storage systems are essential in this case. Moreover, platforms like Tableau can be used to render live updates on interactive dashboards or trigger automated code actions directly within the software. However, it is difficult to ensure data consistency when processing large amounts of data, so various advanced technologies are used. Real-time analytics become crucial in enabling immediate responses to rapidly changing data, as they support applications such as traffic monitoring, fraud detection, and predictive maintenance.

5.5 Cost & Infrastructure (J_5)

The cost and infrastructure of data analytics are the main hurdles when working with large and complex datasets. Organizations invest in powerful hardware, storage systems, networking resources and software tools to support data processing operations. Serverless pipelines are used to automatically scale and charge for each processed event. Often, the increasing amount of data is measured through scalable infrastructures such as cloud computing platforms and distributed systems, which can significantly increase operational costs. Small and medium-sized organizations often face difficulties in allocating sufficient budgets for advanced analytics solutions, which often do not ensure high performance, reliability and data availability in the infrastructure. Therefore, to overcome these difficulties, skilled professionals are also needed to manage and maintain the analytical environment. System failures, slow processing and reduced productivity can harm data analytics [51]. Therefore, balancing cost and infrastructure requirements is essential for sustainable data analytics.

5.6 Skill Gap & Communicating Results (J_6)

While data professionals may have the coding skills to uncover insights, they lack the business knowledge required to execute on those insights, a gap known as the "last-mile" problem. Therefore, skills gaps in data analysis [11] and presenting results are significant barriers. Statistics, programming, data management and analytics are critical for effective data analysis through various advanced trainings, such as real-time OLAP databases, automated pipelines and generative AI prompting. Lack of technical knowledge can lead to mistakes. Analysts transform complex results into clear and understandable information for stakeholders. Because misunderstandings of results can be fatal, they can limit the practical application of analytical insights. Data visualization, reporting and presentation help bridge the gap between data and business objectives. Therefore, overcoming skill gaps and ensuring effective communication becomes essential for successful data-driven data analysis and sound decision-making.

6. Proposed Alternative for Adopting the Challenges for Data Analysis

In real life, proper analysis of data collected from various fields is very important. It usually helps organizations to make informed decisions by transforming raw data into meaningful insights. Here, we have considered six areas of data analysis as alternatives, namely, Business & Marketing , Learning Analytics & Education, Life Sciences & Healthcare, Environment & Sustainability, Supply Chain & Operations and Social-Media & Public Opinion, which are discussed below.

6.1 Business & Marketing (D_1)

Business and marketing analytics is an important area of data usage for business decision-making. As organizations track customer behaviour, they base business performance on market trends. Data analytics can improve marketing strategies by identifying customer preferences and speeding up decision-making. It helps businesses ensure optimal utilization of resources and increase profitability. However, analyzing business and marketing data becomes quite challenging due to the large amount of data. Accurate analytics helps organizations achieve competitive advantage, risk management and various strategic plans. Therefore, effective data analytics is crucial for business growth and marketing success.

6.2 Learning Analytics & Education (D_2)

Learning analytics and education data analysis present significant opportunities as well as challenges. Analyzing data from learning management systems (LMS) to enhance student success enables educators to personalize instruction and then help analysts create educational dashboards. The vast amount of data generated by various educational institutions through online learning platforms, tests, attendance records and student activities can be overwhelming. Therefore, this approach helps to identify students' learning styles, monitor their academic performance and identify students who may need additional support. Educational data analysis helps teachers improve teaching strategies and curriculum design, as well as ensure data quality, confidentiality and ethical use of student information. Then the learning analytics plays a crucial role in improving modern educational outcomes.

6.3 Life Sciences & Healthcare (D_3)

Life sciences and healthcare are two major areas of data analytics. To optimize clinical trials, accelerate drug discovery and improve patient outcomes, vast amounts of clinical, genomic and patient data need to be processed. In addition, vast amounts of data are generated from electronic health records, medical imaging and wearable devices. Data analytics can help researchers improve new treatments and drug discovery processes by identifying disease patterns and helping them make accurate diagnoses. Healthcare organizations maintain data quality, privacy and security while optimizing their operations. Then, effective data analytics is essential for the advancement of healthcare services and life science research, as it supports evidence-based medical decision-making and personalized healthcare.

6.4 Environment & Sustainability (D_4)

Environmental development is an important area where data analytics can help address a range of environmental challenges. Incorporating sustainable development can reduce the environmental footprint and reduce cloud costs. Huge amounts of data collected from satellites, sensors, weather stations and environmental monitoring systems are analyzed to monitor climate change and pollution levels. This enables researchers to identify environmental trends and assess the impact of human activities on the environment. While analytical insights help make better decisions for energy management, conservation and waste reduction, managing large volumes of environmental data can be challenging. Therefore, data analytics plays a crucial role in protecting the environment and achieving long-term development goals by improving sustainable planning and enabling accurate analytical forecasts.

6.5 Supply Chain & Operations (D_5)

Supply chain and operations are important areas of data analytics, where improved decisions are made through efficiency and productivity. It is essentially the practice of evaluating logistical, inventory and procurement data to forecast demand, optimize processes and reduce costs. Essentially, by analyzing the vast amounts of data that organizations generate from procurement, transportation and manufacturing processes, businesses can reduce operational costs while forecasting demand. It helps improve overall supply chain performance by identifying bottlenecks by summarizing historical data (e.g., historical sales or warehouse inventory levels) to identify past trends. Furthermore, real-time analytics help organizations respond quickly to changing market conditions by providing analytical insights that aid in better planning and risk management. However, integrating data from multiple sources and ensuring its accuracy is challenging, making effective supply chain management and operational excellence essential.

6.6 *Social-Media & Public Opinion* (D_6)

Social media and public opinion are extremely important areas for data analysis, as they provide real-time, global insights into people's thoughts, preferences and behaviours. By analyzing the vast amount of data generated daily through social media posts, comments, reviews and online interactions, organizations can understand public opinion and identify emerging trends. As a result, brand reputation increases. This not only improves business but also helps governments make informed decisions based on public opinion. Trend detection determines consumer preferences and sentiment analysis reveals social issues. However, data analysis is challenging because social media data is often unstructured, messy and rapidly changing. Overall, it plays a crucial role in effectively understanding and responding to public opinion.

7. Model Structure and Data Collection

This section discusses the model formulation and data collection process in detail. First, we formulate the model with appropriate criteria and alternatives, followed by the data sources and the collection procedure of the challenges of data analysis studies.

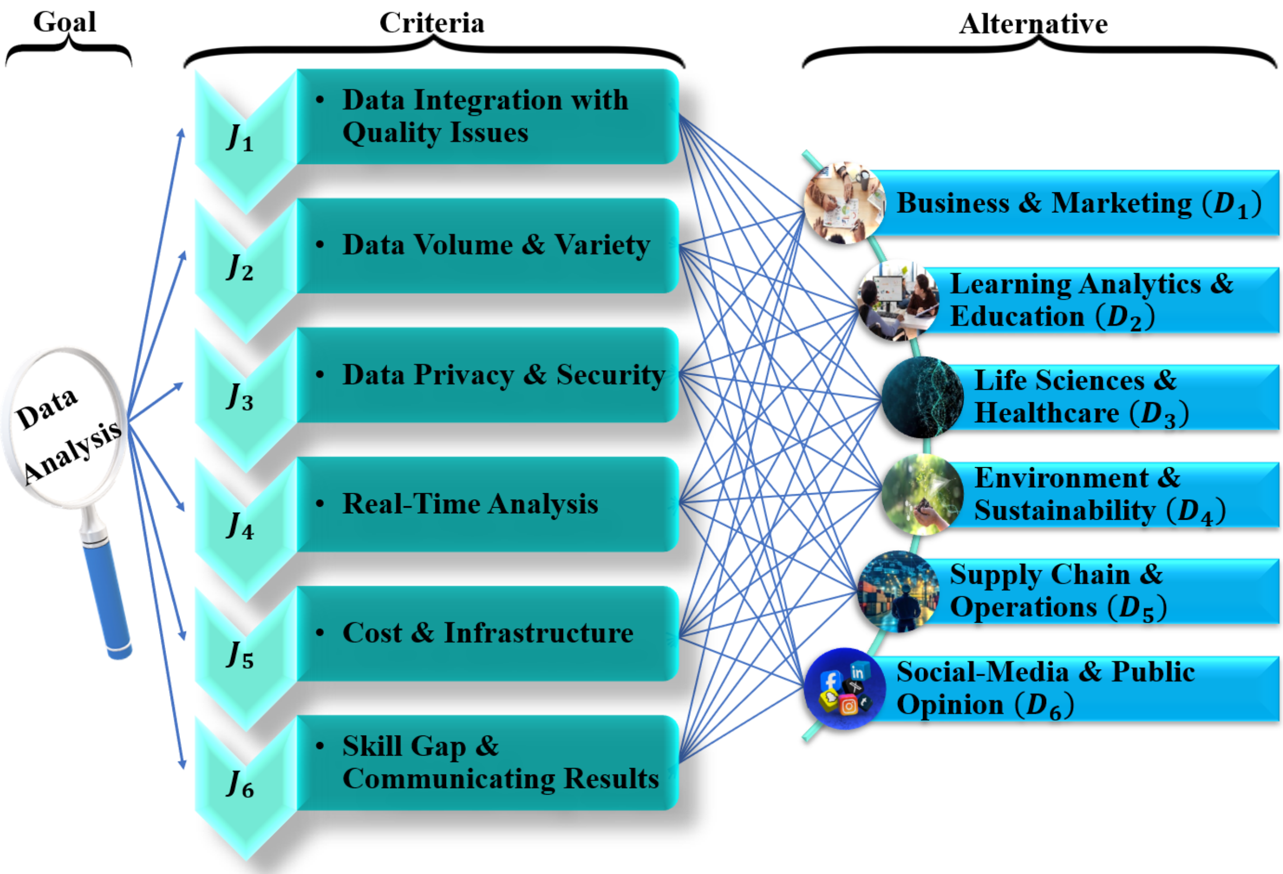

Fig. 7. Hierarchical structure of the proposed data analysis model

7.1 Model formulation

This portion mainly describes the formulation of this proposed work. There are six criteria considered for identifying the most appropriate challenges for data analysis, as outlined in Section 5.1, with six different areas of data analysis are presented as alternatives, which are discussed in Section 5.2. Then, the decision matrices are ordered in a 6×6 manner in linguistic terms and further converted into TrIFNs using a conversion table. The hierarchical structure of this proposed model of data analysis challenges is shown in Figure 7.

7.2 Data collection

The data collection of these challenges in the data analysis study is presented in this section. All data are collected in an unbiased, professional manner from three decision-makers (DMs). DMs are experienced and knowledgeable in their respective fields and share their opinions in linguistic terms via decision matrices. The three DMs are as follows:

DM1: a data analyst with more than 10 years of experience in data mining, data sorting, data management and data analysis,

DM2: a company director with more than 15 years of experience in business strategy, financial management and organizational leadership of large data and

DM3: a statistical researcher with more than 8 years of experience in data analysis, research methods and scientific evaluation.

The data are collected from three decision makers (DMs) based on the performance of criteria and alternatives in linguistic terms and further converted into TrIFNs using Table 2. The decision matrices of linguistic terms provided by three DMs are presented in Table 3. This data is utilized in numerical computations in the next sections.

Table 2
Comparison table between linguistic terms and corresponding TrIFNs

Linguistic Terms	Trapezoidal intuitionistic fuzzy numbers (TrIFNs)	De-fuzzification Value
Incredibly Crucial (IC)	$\{(5, 7, 9, 11); 0.8, 0.2\}$	4.8
Very Crucial (VC)	$\{(4, 6, 8, 10); 0.8, 0.2\}$	4.2
Equally Crucial (EC)	$\{(3, 5, 7, 9); 0.8, 0.2\}$	3.6
Minimal Crucial (MC)	$\{(2, 4, 6, 8); 0.8, 0.2\}$	3.0
Below Crucial (BC)	$\{(1, 3, 5, 7); 0.8, 0.2\}$	2.4

Table 3
Decision matrices in linguistic terms given by three DMs

	Criteria vs Alternatives	Data Integration with Quality Issues (J_1)	Data Volume and Variety (J_2)	Data Privacy & Security (J_3)	Real-Time Analysis (J_4)	Cost & Infrastructure (J_5)	Skill Gap and Communicating Results (J_6)
DM 1	Business & Marketing ($\mathcal{D}_1$)	VC	IC	EC	IC	IC	EC
	Learning Analytics & Education ($\mathcal{D}_2$)	MC	VC	BC	EC	BC	IC
	Life Sciences & Healthcare ($\mathcal{D}_3$)	VC	MC	MC	IC	VC	BC
	Environment & Sustainability ($\mathcal{D}_4$)	BC	VC	BC	VC	BC	BC
	Supply Chain & Operations ($\mathcal{D}_5$)	IC	VC	EC	IC	EC	BC
	Social-Media & Public Opinion ($\mathcal{D}_6$)	IC	IC	IC	MC	BC	EC
	Criteria vs Alternatives	J_1	J_2	J_3	J_4	J_5	J_6
DM 2	Business & Marketing ($\mathcal{D}_1$)	IC	IC	EC	VC	IC	VC
	Learning Analytics & Education ($\mathcal{D}_2$)	BC	IC	MC	EC	MC	VC
	Life Sciences & Healthcare ($\mathcal{D}_3$)	VC	VC	BC	VC	IC	BC
	Environment & Sustainability ($\mathcal{D}_4$)	MC	IC	MC	IC	MC	BC
	Supply Chain & Operations ($\mathcal{D}_5$)	VC	VC	EC	VC	EC	MC
	Social-Media & Public Opinion ($\mathcal{D}_6$)	VC	BC	VC	BC	BC	EC
	Criteria vs Alternatives	J_1	J_2	J_3	J_4	J_5	J_6
DM 3	Business & Marketing ($\mathcal{D}_1$)	VC	VC	VC	IC	IC	EC
	Learning Analytics & Education ($\mathcal{D}_2$)	MC	IC	MC	EC	MC	VC
	Life Sciences & Healthcare ($\mathcal{D}_3$)	IC	IC	BC	IC	IC	MC
	Environment & Sustainability ($\mathcal{D}_4$)	MC	MC	BC	IC	BC	MC
	Supply Chain & Operations ($\mathcal{D}_5$)	VC	IC	EC	VC	VC	MC
	Social-Media & Public Opinion ($\mathcal{D}_6$)	VC	VC	VC	BC	BC	EC

8. Numerical Illustration and Discussion

Numerical computations of this proposed data analysis study are conducted in this section. The related criteria and alternatives for these challenges in data analysis studies are discussed in Section 5 and Section 6, respectively. Two MCDM methodologies are considered for this calculation process under the TrIFNs environments. First, evaluate the weights of the criteria, followed by the ranking of the alternatives. Details discoustion of this numerical process are presented as follows:

First, evaluate the weights of the different factors in the challenges of data analysis studies using the entropy weighted method, as described in Section 4.1, in the TrIFNs environments (see Section 3). Data sets are provided in linguistic terms in Table 3 and decoded into TrIFNs by the conversion table presented in Table 2. The entropy weighted method performed as follows: The decision matrices $(\tilde{\mathcal{A}}_\delta)$ from the three DMs are aggregated into a single decision matrix $(\tilde{\mathcal{A}})$ with the help of Equation (17). Further, $\tilde{\mathcal{A}}$ is converted into a de-i-fuzzified aggregated decision matrix by using Equation (13) and shown in Table 4. Then evaluate the normalized modified decision matrix using Equation (19) and presented in Table 5. After that, the entropy value and degree of dissatisfaction of each criterion are evaluated by using Equation (20) and Equation (21) and shown in Table 6, respectively. Finally, the weights of the criteria of this data analysis study are calculated from Equation (22) and presented in

Table 6.

Table 4
De-i-fuzzified aggregated decision matrix

Criteria vs Alternatives	J_1	J_2	J_3	J_4	J_5	J_6
Business & Marketing (D_1)	4.400	4.600	3.800	4.600	4.800	3.800
Learning Analytics & Education (D_2)	2.800	4.600	2.800	3.600	2.800	4.400
Life Sciences & Healthcare (D_3)	4.400	4.000	2.600	4.600	4.600	2.600
Environment & Sustainability (D_4)	2.800	4.000	2.600	4.600	2.600	2.600
Supply Chain & Operations (D_5)	4.400	4.400	3.600	4.400	3.800	2.800
Social-Media & Public Opinion (D_6)	4.400	3.800	4.400	2.600	2.400	3.600

Table 5
Normalized modified decision matrix

Criteria vs Alternatives	J_1	J_2	J_3	J_4	J_5	J_6
Business & Marketing (D_1)	0.190	0.181	0.192	0.189	0.229	0.192
Learning Analytics & Education (D_2)	0.121	0.181	0.141	0.148	0.133	0.222
Life Sciences & Healthcare (D_3)	0.190	0.157	0.131	0.189	0.219	0.131
Environment & Sustainability (D_4)	0.121	0.157	0.131	0.189	0.124	0.131
Supply Chain & Operations (D_5)	0.190	0.173	0.182	0.180	0.181	0.141
Social-Media & Public Opinion (D_6)	0.190	0.150	0.222	0.107	0.114	0.182

Table 6
Criteria weight and associated data evaluated by using entropy weighted method

Criteria	Sum	EI	DI	**Weight**
Data Integration with Quality Issues (J_1)	-0.769	0.989	0.011	0.1671
Data Volume & Variety (J_2)	-0.777	0.998	0.002	0.0230
Data Privacy & Security (J_3)	-0.769	0.988	0.012	0.1743
Real-Time Analysis (J_4)	-0.770	0.990	0.010	0.1517
Cost & Infrastructure (J_5)	-0.762	0.979	0.021	0.3096
Skill Gap & Communicating Results (J_6)	-0.769	0.988	0.012	0.1743

Table 6 represents the weights of the criteria determined by using the entropy weighted method under TrIFN environments and graphically represented through the Pi diagram in Figure 8. From the above results, we can see that the Cost & Infrastructure (J_5) criteria is the optimal criterion for this challenges of data analysis study, followed by Data Privacy & Security (J_3), Skill Gap & Communicating Results (J_6), Data Integration with Quality Issues (J_1) and Real-Time Analysis (J_4), respectively. Finally, the criteria Data Volume & Variety (J_2) is the least weighted criteria for this study. These results are further utilized to prioritize the alternatives.

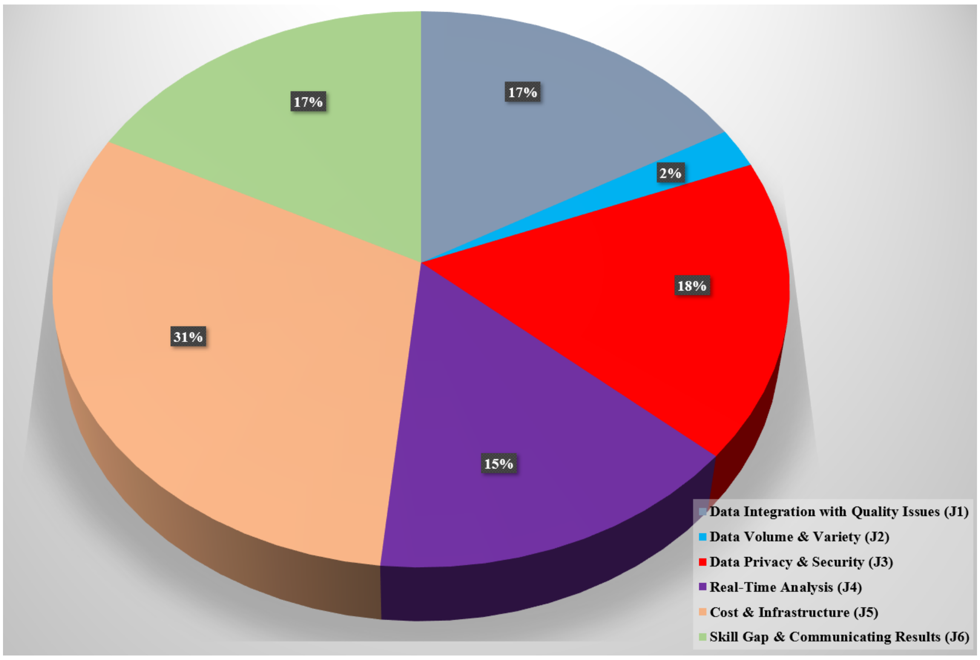

Fig. 8. Weights of the criteria evaluated by the entropy weighted method

Now, we determine the ranking of the alternatives in this data analysis study using the VIKOR methodology, presented in Section 4.2, in the TrIFNs environments (see Section 3). Data sets are described in linguistic terms in Table 3 and converted into TrIFNs using the conversion table shown in Table 2. The VIKOR method performed as follows: The de-i-fuzzified aggregated decision matrix evaluated in the previous section is considered for and shown in Table 4. Then the best value $(\mathcal{P}_\omega)$ and worst value $(\mathcal{Q}_\omega)$ of the each criteria (ω) is calculated by using Equation (23) & Equation (24) and presented in Table 7. Further, determine the weighted relative distance in Table 8. The $\mathcal{R}_\sigma$ and $\mathcal{S}_\sigma$ values are calculated by using Equation (25) and Equation (26) and presented in Table 9, respectively. Finally, determine the $\mathcal{T}_\sigma$ values of each alternative using Equation (29) and based on rank the alternatives. The rank of the alternatives with associated values is shown in Table 9.

Table 7

The best value $(\mathcal{P}_\omega)$ and worst value $(\mathcal{Q}_\omega)$ of the criteria (ω)

Criteria	J_1	J_2	J_3	J_4	J_5	J_6
Best value $(\mathcal{P}_\omega)$	4.400	3.800	4.400	4.600	2.400	4.400
Worst value $(\mathcal{Q}_\omega)$	2.800	4.600	2.600	2.600	4.800	2.600

Table 8

Weighted relative distance among the alternatives from best and worst values

Criteria vs Alternatives	J_1	J_2	J_3	J_4	J_5	J_6
Business & Marketing (D_1)	0.000	0.023	0.058	0.000	0.310	0.058
Learning Analytics & Education (D_2)	0.167	0.023	0.155	0.076	0.052	0.000
Life Sciences & Healthcare (D_3)	0.000	0.006	0.174	0.000	0.284	0.174
Environment & Sustainability (D_4)	0.167	0.006	0.174	0.000	0.026	0.174
Supply Chain & Operations (D_5)	0.000	0.017	0.077	0.015	0.181	0.155
Social-Media & Public Opinion (D_6)	0.000	0.000	0.000	0.152	0.000	0.077

Table 9
Alternative ranking with associated values by the VIKOR method

Alternatives	$\mathcal{R}_\sigma$	$\mathcal{S}_\sigma$	$\mathcal{T}_\sigma$	Ranking
Business & Marketing (D_1)	0.449	0.310	0.769	5
Learning Analytics & Education (D_2)	0.472	0.167	0.346	2
Life Sciences & Healthcare (D_3)	0.638	0.284	0.918	6
Environment & Sustainability (D_4)	0.547	0.174	0.460	4
Supply Chain & Operations (D_5)	0.445	0.181	0.356	3
Social-Media & Public Opinion (D_6)	0.229	0.152	0.000	1

The ranking of the alternatives to these challenges of the data analysis study is shown in Table 9 and graphically depicted through the Bar diagram in Figure 9. The optimal values of $(\mathcal{R}_\sigma)$ and $(\mathcal{S}_\sigma)$ are $\mathcal{R}^+ = 0.638$, $\mathcal{R}^- = 0.229$, $\mathcal{S}^+ = 0.310$ and $\mathcal{S}^- = 0.152$. From the evaluated results, Social-Media & Public Opinion (D_6) be the most prioritized alternatives, followed by Learning Analytics & Education (D_2), Supply Chain & Operations (D_5), Environment & Sustainability (D_4) and Business & Marketing (D_1), respectively. Further, Life Sciences & Healthcare (D_3) is the least optimal alternative for this data analysis challenged study.

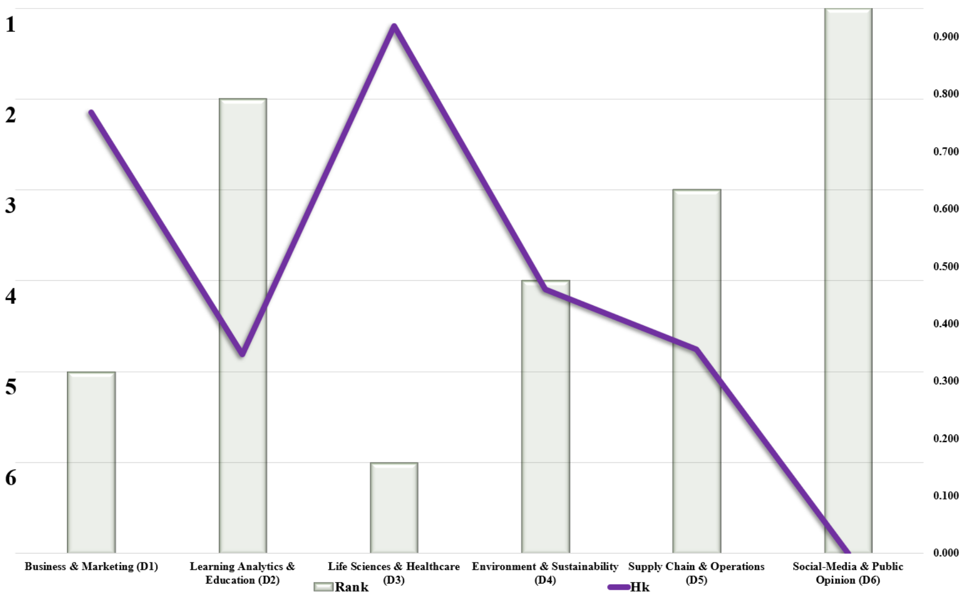

Fig. 9. Ranking of the alternative determined by the VIKOR method

9. Comparative Analysis

This section presents a comparative analysis of the proposed study to assess the consistency and flexibility of the results. This was conducted using multiple MCDM methods, namely TOPSIS [57] and COPRAS [58]. These methods are also very popular and calculate the ranking of the alternatives based on different approaches. The evaluated results are shown in Table 10 and graphically depicted in Figure 10.

Table 10
Ranking of the alternatives through comparative analysis

Alternative	TOPSIS	COPRAS	VIKOR
Business & Marketing (D_1)	5	3	5
Learning Analytics & Education (D_2)	2	2	2
Life Sciences & Healthcare (D_3)	6	6	6
Environment & Sustainability (D_4)	4	5	4
Supply Chain & Operations (D_5)	3	4	3
Social-Media & Public Opinion (D_6)	1	1	1

Table 10 presents a comparative analysis of these challenges in data analysis studies using the TOPSIS and COPRAS methodologies. Based on the evaluation results, the TOPSIS and VIKOR methods yield the same ranking of the alternatives, whereas the COPRAS method produces slightly different ranks. From the COPRAS method, alternatives D_2, D_3 and D_6 give the same rank of the main results; however, alternatives D_1, D_5 and D_4 interchange their rank with respect to the main results. The rankings of the alternatives using the TOPSIS and COPRAS methods, along with the main results (ranking of the VIKOR method), are presented in a bar diagram in Figure 10.

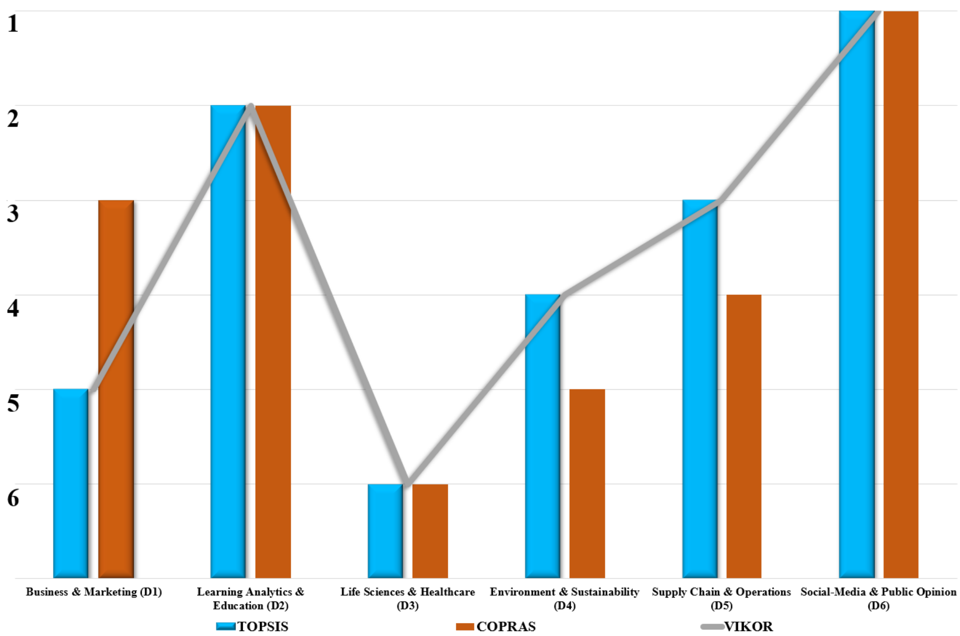

Fig. 10. Ranking of the alternatives by TOPSIS and COPRAS methods

10. Research Implication

This research has a significant impact on the various institutions to navigate any complex and large data landscapes by developing a framework in fuzzy MCDM structured to identify, sort and prioritize the optimal criteria and alternatives of data analysis barriers. This research efficiently manages accounts for real-world uncertainty, ambiguity in the data set and subjective human opinions. The study enables any organizations to step aside from any form of guesswork and strategically distribute limited resources, such as workers, budget, time and talent, in the direction of resolving the most significant bottlenecks. Further, integrating fuzzy set theory reduces strategic risks by mitigating errors arising from simplified or inaccurate assumptions. Ultimately, this model serves as an unbiased and robust flowchart for professionals and researchers, connecting the gap between quantitative accuracy and qualitative comprehension to foster smarter, data-driven decision-making and more robust analytics systems. This optimization approach can be utilized by business owners, various entrepreneurs, stakeholders, police makers and different institutional works to mathematically rank and optimize their difficult data.

11. Conclusions and Future Research Scope

This section describes the conclusion of this study elaborately. The evaluated results are discussed and analysed in detail in Section 8. This research provides a comprehensive analysis of various challenges of data analysis. It gives companies a smart and modern way to find out exactly which data problems they should fix first and so on. Instead of listening or guessing to whoever screams the loudest, here we used a computational based system that handles the uncertain, confusing and opinion based challenges that various institutions and businesses face in recent times. This model can help any organization to reduce the waste of time, resources and money on the old technologies and guide them to focus their energy on the right things and make an impactful change.

11.1 *Shortcomings of this study*

The shortcomings of this fuzzy MCDM study are discussed in this section. This proposed model evaluates by maintaining ambiguity; it bears with a reliance on the extremely subjective decision of experts' input, any personal bias or lack of experience of the subject matter. Further, the model exhibits various computational complexities that cause it to scale poorly as the number of criteria and alternatives increases. This model is a completely opinion-based model, which is a major drawback that may be overcome by increasing the number of decision makers.

11.2 *Future research scope*

This section discusses the future research scope of this study. This study was conducted using six criteria and six alternatives, which can be expanded even include sub-criteria for better computation. Fourth, for unsanitary capture, we may use a neutrosophic set or a picture fuzzy set to address the hesitancy and neutrality in the data set and the proposed model. Only two MCDM methods were used in this study; however, the number can be increased, depending on the model, to verify the accuracy of the results. A sensitivity analysis may be conducted to check the flexibility and robustness of the evaluated results.

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Conflicts of Interest

The authors declare no conflicts of interest.

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