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Evaluating and Ranking Metaverse Platforms Using Intuitionistic Trapezoidal Fuzzy VIKOR MCDM: Incorporating Score and Accuracy Functions for Comprehensive Assessment

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ABSTRACT

The purpose of this study is to develop a new approach of decision-making for addressing multi-attribute decision-making problems within a trapezoidal intuitionistic fuzzy environment, while taking into account decision makers' psychological behavior. As a starting point, we propose and apply a distance metric model for trapezoidal intuitionistic fuzzy numbers. Then, by incorporating the expected value, score function, and accuracy value, we create a novel approach by comparing it with the results obtained from the VIKOR multi-criteria decision-making technique, allowing us to account for decision makers' risk tolerance. Through correlation analysis, we assess the similarities and deviations in the resulting rankings. Finally, we illustrate the practical utility and feasibility of our proposed approach by evaluating the digital marketing capabilities of a few metaverse platforms using standards set in line with marketing mix criteria.

1. Introduction

The emergence of metaverse platforms has brought forth a new era of immersive digital experiences, enabling users to interact, socialize, and engage within virtual environments. With the increasing number of metaverse platforms available, selecting the most suitable one for specific needs becomes a complex decision-making task. To facilitate a comprehensive assessment and ranking of these platforms, the Trapezoidal Intuitionistic Fuzzy VIKOR (VlseKriterijumska Optimizacija I Kompromisno Resenje) multi-criteria decision-making (MCDM) method, incorporating score and accuracy functions, proves to be a valuable approach. This method allows decision-makers to evaluate and rank metaverse platforms based on multiple criteria, considering both qualitative and quantitative factors. By incorporating fuzzy evaluation, score function, and accuracy function, this approach enables a more robust and realistic evaluation process, considering the inherent uncertainties and subjectivity involved in decision-making.

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The score function assigns scores to each alternative based on the performance of metaverse platforms across various criteria, reflecting their relative importance. These scores provide a quantitative measure of the platforms' performance and facilitate comparison. The accuracy function measures the proximity of each platform to the ideal solution, considering the inherent fuzziness and imprecision associated with the evaluation process. It enables decision-makers to assess how closely each platform aligns with the desired criteria, thereby enhancing the accuracy and reliability of the evaluation. By incorporating the score and accuracy functions into the Trapezoidal Intuitionistic Fuzzy VIKOR MCDM method, decision-makers can conduct a comprehensive assessment of metaverse platforms, considering both objective and subjective factors. This approach assists in ranking the platforms and identifying the most suitable option based on the desired criteria, ultimately aiding in informed decision-making when selecting a metaverse platform.

By merging the score and accuracy function values within the VIKOR framework, this research presents a novel technique. By taking into account both quantitative and qualitative factors, this integration improves the method's resilience while simultaneously increasing its sensitivity to uncertainty and its capacity to capture the complex preferences of decision-makers. Our method offers a comprehensive solution that considerably advances the viability and application of the VIKOR method by bridging the gap between quantitative performance measures and qualitative evaluation.

In this context, this article aims to provide insights into the evaluation and ranking of metaverse platforms using the Trapezoidal Intuitionistic Fuzzy VIKOR MCDM method, highlighting the significance of incorporating score and accuracy functions to conduct a comprehensive assessment. A numerical example will be presented to demonstrate the practical application of this approach, showcasing how decision-makers can effectively evaluate and rank metaverse platforms to make informed choices in the dynamic and evolving metaverse landscape.

2. Literature Survey

Making judgements while taking into account several frequently contradictory criteria is referred to as MCDM. MCDM involves the evaluation of attribute data to make an acceptable choice. This technique allows decision makers (DMs) to choose the best alternative and/or rate the entire set of workable alternatives in light of the decision matrix. Thus far, a number of MCDM techniques have been presented and successfully used to address complex decision-making issues emerging from many management and technical fields. Fuzzy decision-making is employed when there are ambiguous or insufficient data to support the solution. Applications for fuzzy MCDM (FMCDM) approaches are numerous; they are used differently in diverse situations. The idea of fuzzy sets was introduced by Zadeh [1] as a way to address these fuzzy occurrences in practical issues. The fuzzy multi-attribute decision-making methods based on fuzzy sets have been substantially researched and used in numerous sectors, because Zadeh's fuzzy sets can better portray the fuzziness of the objective items themselves and of human thinking. There are certain restrictions to these fuzzy sets in many practical decision-making problems, as they can only reflect two elements of information and has only one degree of membership. As a result, Atanassov [2] developed Zadeh's theory of fuzzy sets and proposed the idea of intuitionistic fuzzy (IF) set. The VIKOR method is extended in intuitionistic fuzzy environment, aiming at solving MCDM problems in whichthe weights of criteria and ratings of alternatives aretaken as a triangular intuitionistic fuzzy set [3]. A new method is proposed to solve multi-criteria group decision-making (GDM) problems, in which both the criteria values and criteria weights take the form of linguistic information based onthe traditional idea of the VIKOR method. The linguistic criteria weights given by all DMs are transformed into trapezoidal fuzzy numbers and then aggregated and defuzzied to crisp values [4]. The VIKOR method is extended with a stability analysis determining the weight stability intervals and with trade-offs analysis [5]. Gupta et al. [6]

presented a new decision-making method for multi-attribute GDM (MAGDM) problems in general and plant location selection (PLS) problems in particular, with intuitionistic fuzzy information captured through trapezoidal intuitionistic fuzzy numbers (TrIFNs). The classical VIKOR method was extended to solve MAGDM problems under the intuitionisticfuzzy environment based on TrIFNs. Tavana et al. [7] proposed a risk-based stochastic VIKOR (RB-VIKOR) model that accounts for differences in the risk attitudes of DMs when ranking stochastic alternatives. They presented a case study in the banking industry to illustrate how differences in the risk attitudes ofDMs condition the rankings obtained. Moreover, they compared their findings with those derived from a stochastic super-efficiency data envelopment analysis model to demonstrate the applicability and efficiency of RB-VIKOR. For MCDM issues, a trapezoidal intuitionistic fuzzy aggregation operator based on the Choquet integral was suggested in this study [8]. The decision-making information is shown as TrIFNs and takes into account both the significance of the decision-making criteria and their interactions. In this research, a novel weight allocation method based on the standard deviation (SDV) metric is proposed. The idea of the centroid point is used to create a new ranking algorithm for TrIFNs. The centroid location for TrIFN is also defined for this reason. The proposed centroid formulae's justification is demonstrated. Additionally, the ranking approach is used to solve a problem involving MCDM, where the ratings of the options on each criterion are expressed using TrIFNs [9]. TrIFNs' expected values, score function, and accuracy function are defined. A sort of intuitionistic trapezoidal fuzzy MCDM system is suggested based on these. In order to obtain flexible allocation of machine tool dependability, Cheng et al. [10] integrated TrIFNs with the performance sorting technique based on related ideal solutions. The VIKOR method, a well-known MCDM strategy that placed an emphasis on selecting and ranking alternative sets of competing criteria, was first established by Opricovic and Teng (Opricovic&Teng,2007). In recent years, scientists have further developed this technique. Samantra et al. [11] used the fuzzy VIKOR method by representing the ratings and weights as triangular fuzzy numbers for supplier selection problems. Sayadi et al. [12] introduced the idea of optimism level of DM to solve decision-making problems with interval data using an extended VIKOR method. In this study, the hybrid FUCOM–Z-number–multi-attributive border approximation area comparison (MABAC) model was used to conduct the selection procedure. The weight coefficients of the selection criteria were established using the FUCOM approach. To rank alternatives, the MABAC approach was modified by using a Z-number. The final results showed that the use of Z-numbers in decision-making encompasses a wider range of uncertainty than the use of regular fuzzy numbers, which is crucial for making choices in battle circumstances [13].

The ranking of Critical Success Factors (CSF) in charge of the CERP has been determined using the analytic hierarchy process (AHP)- and fuzzy AHP (FAHP)-based modelling techniques. The decision-making model was also constructed using AHP based on GDM [14]. In this study, FDOSM was expanded into the Fermatean-FDOSM mathematical model to further benchmark the real-world issue. The Fermatean-FDOSM mathematical model, which consists of three phases of FDOSM, is presented in the first phase. The new expansion was used in the second phase to compare the COVID-19 machine learning techniques [15]. The methodology used in this study replaces the conventional intuitive ratings of PR services with multi-circular decision-making using the FAHP–Z-number model–fuzzy MABAC for the selection of online media used by public administration when connecting with citizens [16]. This study suggested the BWM technique to determine the relative importance of factors considered in the evaluation of possible off-road vehicles for the needs of SAF. The MABAC and MAIRCA methods were used in this study through result validation in addition to the COPRAS approach, which is a part of the fundamental decision-making model [15]. A novel MCDM framework is suggested in this study for assessing the operational effectiveness of logistics service providers. The novel logarithm methodology of additive weights (LMAW), conducted in six steps, was used to evaluate the alternatives [17]. Biswas and Pamucar [18] presented a novel grey correlation-based picture fuzzy evaluation based on distance from average solution (GCPF-EDAS) framework for the comparison analysis and also incorporated the essential framework of the technology acceptance model and the unified theory of acceptance and usage of technology vis-à-vis service quality characteristics for criterion selection. In this work, the RSO algorithm was introduced, a mapping strategy was developed, mathematical operators were redefined, a technique to improve the quality of solutions was proposed, the algorithm's effectiveness was demonstrated through simulations and comparisons, and its performance was then verified through statistical analysis [19]. In this study, triangular fuzzy numbers were used to modify the LMAW method. The adjustment considerably increased the LMAW method's ability to take uncertainty into account while making decisions. The method's unique significance can be seen in the relatively straightforward mathematical framework that makes it possible to identify and rank alternative solutions in uncertain situations with high-quality weight coefficients for criteria [20]. The study suggested a decision-making strategy to prioritize four connected autonomous vehicles with self-powered sensing options. The model uses a fuzzy complete consistency approach and a fuzzy non-linear model to evaluate alternatives based on technical advancement, environmental, implementation, and economical aspects [21]. To compare the market performance of metaverse crypto assets based on factors such as return, momentum, market capitalization, trading volume, and risk, the study introduced a novel hybrid decision-making framework called LOPCCSA. Even when the performance values in the decision matrix were negative, the framework could produce a consistent and trustworthy conclusion [22]. The potential of the metaverse, a 3D digital environment that combines the actual and virtual worlds, in education was covered in the study. It offers a precise description, conceptual framework, feature set, prospective uses, difficulties, and areas for further research on metaverse in education [23]. Mohammed et al. [24] suggested a paradigm for exploiting the bitcoin network's anonymity and privacy capabilities to create the metaverse in Industry 5.0. The best strategy was determined by the model's combination of the fuzzy weighted with zero inconsistency method, Diophantine linear fuzzy sets, multi-objective optimization based on ratio analysis, and the multiplicative form (MULTIMOORA). To rank the neutrosophic sets, which contain ambiguous or unclear information recorded in three variables, Singh and Bhat [25] proposed a novel score and accuracy function by creating an MCDM process using the suggested functions. In the context of the enhanced multi-dimensional complicated Fermatean fuzzy N-soft set, this work sought to present a novel decision-making strategy while preserving the intriguing characteristics of the traditional VIKOR method. The ability of the complicated Fermatean fuzzy N-soft set to capture two-dimensional uncertain and imprecise information, as well as the multi-valued parameters, was its key feature [26].

With the development of technology, the digital transformation process experienced worldwide manifests itself in all areas of life. Digital transformation processes, which play an important role in changing all social and economic habits, also create great opportunities in many areas. Depending on this digital transformation, the popularity of digital marketing activities is increasing, and investments, both individual and commercial, are shifting towards this field. Investments and steps taken depending on the suitability of their technological infrastructures enable companies to differentiate against their competitors. Especially with the active use of social media in digital marketing strategies, the competitive advantage of companies has started to gain a different dimension with the integration of the concept of virtual reality into business activities today. Sebastian [27] suggested methods based on the technological acceptance model that might enhance perception and lessen worries about this technology, facilitating quicker adoption and use. The uniqueness of the study lies in its conceptual model, which links both technological and personal factors. Additionally, in the present study, deep learning-based analysis of structural equation modelling (SEM) and artificial neural network will be conducted using the innovative hybrid analytic method (ANN) [28]. To determine whether the change is as drastic as described or instead represents an incremental transformation of the current BM, the goal of this study is to investigate Facebook's announced changes in its BM [29]. Metaverse, which aims to help individuals or businesses connect, create communities, and grow their businesses, stands out among digital marketing tools with these features [30]. According to the authors, augmented reality marketing is a novel, strategically sound, and potentially disruptive marketing subdiscipline. In addition, they suggest the BICK FOUR framework (branding, inspiring, convincing, and keeping) as a means of organizing pertinent objectives as they explore a sophisticated customer journey model for AR marketing strategy [31]. The metaverse concept consists of the combination of the words "meta", which expresses an abstract (virtual) idea in English, and "universe", which corresponds to the universe, and is defined as augmented virtual reality [32]. The term “metaverse” was first mentioned in the science fiction book “Snow Crash,” written by American author and technology consultant Neal Stephenson in 1992 [29]. Di Pietro & Cresci [33] made various contributions in this study, by examining the metaverse's theoretical underpinnings and concentrating on the novel privacy and security concerns raised by this new paradigm, before broadening the contribution's focus and highlighting some of the far-reaching yet logical implications of the metaverse on a variety of domains, not all of them in technology. Considering the promotion of purchase in virtual commerce contexts, this study used a systematic literature review technique to synthesize studies on virtual commerce from both application design and consumer behavior research [34]. Museums are unsatisfactory as experiencing venues due to the lack of contact with visitors and use of lighting that clearly distinguishes actual from virtual settings. Choi and Kim [32] presented a strategy for deploying content services for visitors' museum experiences by fusing beacons and HMDs to address such issues. Fitria and Simbolon [35] demonstrated the potential of the metaverse, which will probably allow for the eventual implementation of virtual worlds for all educational activities. As new learning experiences grow more authentic and meaningful, it is necessary to use students' preparation while implementing the metaverse technology in the classroom. Virtual reality technologies integrated with metaverse platforms offer businesses the chance to improve attitudes toward their brands and encourage positive behaviors while simultaneously giving users a communication extension thanks to its complexity, flexibility, and immersiveness in terms of the technologies used [36]. Virtual reality technologies, which are used in a wide range of industries including tourism, are based on recognition and enable users to move around as they would in the real world using visual and auditory stimuli [37]. Digital representations made by users on metaverse platforms that may be customized and signify the presence of the user are known as avatars, which are generic graphical designs that are individualized by computer technologies. Korkeila and Hamari examined the relationship between characteristics connected to gaming interests and the types of capital (economic, cultural, social, and symbolic) [38]. Diego-Mas and Alcaide-Marzal [39] developed a method for creating avatar faces that can express to the viewer the emotions most appropriate to the situation. The suggested system was built using a hybrid of genetic algorithms and artificial neural networks, whose training was based on how people perceive a set of faces. This study looked at how the aforementioned characteristics might affect digital self-representations known as avatars. Two avatars were produced by 94 participants to be used in various scenarios—video game- and job-themed social network [40].

3. Description of the methodology applied

3.1 Model description

The model described in this research deals with evaluating and ranking metaverse platforms. Finding a fix for this issue is specific due to the amount of ambiguity. The first set of uncertain factors occurs when the criteria for the metaverse platforms are established. To reduce ambiguity in the decision-making process, triangular intuitive fuzzy numbers are used. The score and accuracy function, which combine to create a quantitative decision framework, are essential to the MCDM technique. They help DMs choose solutions that are in line with their tastes and aims by making it simpler to analyze options while taking into consideration a range of aspects. The ranking is determined using the score and accuracy function. In addition, the idea of the VIKOR index, which combines the score and accuracy function, is used to rank the alternatives. By merging the score and accuracy function, the VIKOR technique may successfully manage a variety of criteria and provide a well-balanced compromise that suits the DM's preferences.

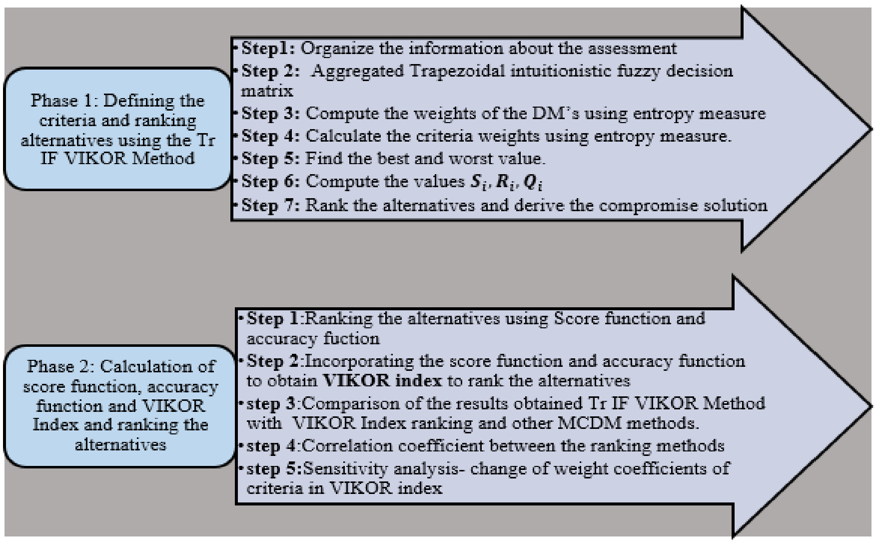

Fig. 1. General overview of the model for metaverse ranking

Figure 1 illustrates the two phases of the model: Phase 1 defines the criteria and ranking using the TrIF VIKOR method. Phase 2 involves comparison of the results with the VIKOR index ranking.

3.2. Preliminaries

Definition 1. An intuitionistic fuzzy set A is defined in the universe of discourse X as $A = \{\langle x, \mu A(x), \vartheta A(x)\rangle / x \in X\}$ .On the condition that $\mu A(x), \vartheta A(x): X \rightarrow [0,1]$ represent the membership and non-membership functions, respectively, and $0 < \mu A(x) + \vartheta A(x) \leq 1$. In addition, the intuitionistic fuzzy index $\pi A(x)$, which expresses whether or not x belongs to A. $\pi A(x) = 1 - \mu A(x) + \vartheta A(x)$ is developed by IFS [2].

Definition 2. Let $a, b, c, d \in R, 0 \leq \mu_{\tilde{a}} \leq 1, 0 \leq \vartheta_{\tilde{a}} \leq 1, and\ \mu_{\tilde{a}} + \vartheta_{\tilde{a}} \leq 1$. A fuzzy number $\tilde{a} = ([a, b, c, d]; \mu_{\tilde{a}}, \vartheta_{\tilde{a}})$ is called a TrIFN if its membership and non-membership degree functions are [41]

$$\lambda_{\tilde{a}}(x) = \begin{cases} \mu_{\tilde{a}}(x-a)/(b-a), a \leq x < b \\ \mu_{\tilde{a}}, \quad b \leq x \leq c \\ \mu_{\tilde{a}}(d-x)/(d-c), c < x \leq d \\ 0, \quad other \end{cases}$$

$$\boldsymbol{\gamma}_{\tilde{a}}(\boldsymbol{x}) = \begin{cases} (\boldsymbol{b}-\boldsymbol{x}) + \vartheta_{\tilde{a}}(x-a)/(b-a), \boldsymbol{a} \leq \boldsymbol{x} < \boldsymbol{b} \\ \vartheta_{\tilde{a}}, \quad \boldsymbol{b} \leq \boldsymbol{x} \leq \boldsymbol{c} \\ (\boldsymbol{x}-\boldsymbol{c}) + \vartheta_{\tilde{a}}(d-x)/(d-c), \quad \boldsymbol{c} < \boldsymbol{x} \leq \boldsymbol{d} \\ \boldsymbol{0}, \quad \boldsymbol{other} \end{cases}$$

Definition 3. Let $\tilde{a}_1 = ([a_1, b_1, c_1, d_1]; \mu_{\tilde{a}1}, \vartheta_{\tilde{a}1})$ and $\tilde{a}_2 = ([a_2, b_2, c_2, d_2]; \mu_{\tilde{a}2}, \vartheta_{\tilde{a}2})$ with $\lambda \geq 0$ be two TrIFNs, then the addition of two TrIFNs
$\tilde{a}_1 + \tilde{a}_2 = ([a_1 + a_2, b_1, +b_2, c_1 + c_2, d_1 + d_2]; \mu_{\tilde{a}1} + \mu_{\tilde{a}2} - \mu_{\tilde{a}1}.\mu_{\tilde{a}2}, \vartheta_{\tilde{a}1}.\vartheta_{\tilde{a}2})$

Definition 4. Let $\bar{a}_j (j = 1,2, \dots n)$ be a set of TrIFNs, and TrIFN-WAA:$\emptyset^n \to \emptyset$: if $TrIFN-WAA_\delta(\bar{a}_1, \bar{a}_2, \dots \bar{a}_n) = \sum_{j=1}^{n} \delta_j \bar{a}_j$, where $\emptyset$ is the set of TrIFNs, and $\delta = (\delta_1, \delta_2, \dots \delta_n)^T$ is the weight vector of $\bar{a}_j (j = 1,2, \dots n), \delta_j \in [0,1]$, $\sum_{j=1}^{n} \delta_j = 1$. Then, TrIFN-WAA is called the weighted arithmetic average operator on TrIFNs .

Theorem:
Let $\bar{a}_j = \left([a_j, b_j, c_j, d_j]; \mu_{\bar{a}_j}, \vartheta_{\bar{a}_j}\right) (j = 1,2, \dots n))$, be a set of TrIFNs, then, $TrIFN-WAA_\delta(\bar{a}_1, \bar{a}_2, \dots \bar{a}_n) = \left([\sum_{j=1}^{n} \delta_j a_j, \sum_{j=1}^{n} \delta_j b_j, \sum_{j=1}^{n} \delta_j c_j, \sum_{j=1}^{n} \delta_j d_j]\right); 1 - \prod_{j=1}^{n} \left(1 - \mu_{\bar{a}_j}\right)^{\delta_j}, \prod_{j=1}^{n} \left(\vartheta_{\bar{a}_j}\right)^{\delta_j}$ (1)

where $\delta = (\delta_1, \delta_2, \dots \delta_n)^T$ *is the weight vector of* $\bar{a}_j (j = 1,2, \dots n), \delta_j \in [0,1]$, $\sum_{j=1}^{n} \delta_j = 1$.

Definition 5. Let $\bar{A}\ and\ \bar{B}$ be two TrIFN's $\bar{A} = ([a_1, b_1, c_1, d_1]; \mu_{\bar{A}}, \vartheta_{\bar{A}})\ and\ \bar{B} = ([a_2, b_2, c_2, d_2]; \mu_{\bar{B}}, \vartheta_{\bar{B}})$ and the measure $S_1 = 1 + \mu_{\bar{A}} - \vartheta_{\bar{A}}$; $S_2 = 1 + \mu_{\bar{B}} - \vartheta_{\bar{B}}$.
The distance between $\bar{A}\ and\ \bar{B}$ is given by

$$d(\bar{A}\,\bar{B}) = \frac{1}{8}(|S_1 a_1 - S_2 a_2| + |S_1 b - S_2 b_2| + |S_1 c_1 - S_2 c_2| + |S_1 d_1 - S_2 d_2|) \tag{2}$$

Definition 6. Let $\tilde{a} = ([a, b, c, d]; \mu_{\tilde{a}}, \vartheta_{\tilde{a}})$ be a TrIFN, then the expected value

$$I(\tilde{a}) = \frac{1}{8}(a + b + c + d) \times (1 + \mu_{\tilde{a}} - \vartheta_{\tilde{a}}) \tag{3}$$

Definition 7. The score function typically takes the form of a mathematical function or algorithm that transforms raw data or criteria values of the alternatives into scores. It considers the significance of each criterion by incorporating the weights assigned to them. The purpose of the score is to quantify and represent the performance or quality of each alternative on a common scale, facilitating the comparison and ranking of alternatives. It helps DMs understand the relative strengths and weaknesses of the alternatives in relation to the criteria evaluated [42].
Let $\tilde{a} = ([a, b, c, d]; \mu_{\tilde{a}}, \vartheta_{\tilde{a}})$ be a TrIFN, then the score function is denoted by

$$S(\widetilde{a}) = I(\tilde{a}) \times (\mu_{\tilde{a}} - \vartheta_{\tilde{a}}) \tag{4}$$

where $I(\tilde{a})$ is the expected value of TrIFN $\tilde{a}$.

Definition 8. The accuracy function takes into account the inherent fuzziness and imprecision involved with the evaluation process to determine how close each platform is to the optimal answer. It enables DMs to gauge how closely each platform adheres to the desired standards, thereby improving the evaluation's accuracy and dependability [42].
Let $\tilde{a} = ([a, b, c, d]; \mu_{\tilde{a}}, \vartheta_{\tilde{a}})$ be a TrIFN, then the accuracy function is denoted by

$$H(\widetilde{a}) = I(\tilde{a}) \times (\mu_{\tilde{a}} + \vartheta_{\tilde{a}}) \tag{5}$$

where $I(\tilde{a})$ is the expected value of TrIFN $\tilde{a}$.

4. Tr IF-VIKOR method [Algorithm]

A decision organization with numerous DMs $D_q(q = 1,2, \dots l)$ evaluates the performance of the alternative $A_i \ (i = 1,2, \dots m)$, about the characteristic in an MCDM problem with n options $C_j \ (j = 1,2, \dots n)$. The weights of the matched attributes are represented by $\delta = (\delta_1, \delta_2, \dots \delta_n)^T$, which is the weight vector of $\bar{a}_j (j = 1,2, \dots n), \delta_j \in [0,1], \ \sum_{j=1}^{n} \delta_j = 1$.

Step 1: Organize the information about the assessment in the following manner:
Assume that DMs $D_q(q = 1,2, \dots l)$ express their thoughts on the possibilities for each attribute C_j in terms of linguistic variables, represented as TrIFNs $\bar{a}_j = \left([a_j, b_j, c_j, d_j]; \mu_{\bar{a}_j}, \vartheta_{\bar{a}_j} \right), (j = 1,2, \dots n)$. The evaluations made by the DMs can be written as given in Eq. (6).

$$D^{(q)} = \begin{bmatrix} x_{11}^{(q)} & \cdots & x_{1n}^{(q)} \\ \vdots & \ddots & \vdots \\ x_{m1}^{(q)} & \cdots & x_{mn}^{(q)} \end{bmatrix} \tag{6}$$

where $x_{ij}^{(q)}$ represents the evaluation of the alternative A_i with respect to the criteria C_j .

Step 1.1: The next step involves applying Eq. (7) to normalize the components of the initial decision-making matrix
$x_{ij}^{(q)} = \left([a_j, b_j, c_j, d_j]; \mu_{\bar{a}_j}, \vartheta_{\bar{a}_j} \right), (j = 1,2, \dots n)$, then the normalized value is given by

$$\overline{x_{ij}^{(q)}} = \begin{cases} \left(\left[\frac{a_j}{\max(a_j,b_j,c_j,d_j)}, \frac{b_j}{\max(a_j,b_j,c_j,d_j)}, \frac{c_j}{\max(a_j,b_j,c_j,d_j)}, \frac{d_j}{\max(a_j,b_j,c_j,d_j)} \right]; \mu_{\bar{a}_j}, \vartheta_{\bar{a}_j} \right), & for\ B.C \\ \left(\left[\frac{a_j}{\min(a_j,b_j,c_j,d_j)}, \frac{b_j}{\min(a_j,b_j,c_j,d_j)}, \frac{c_j}{\min(a_j,b_j,c_j,d_j)}, \frac{d_j}{\min(a_j,b_j,c_j,d_j)} \right]; \mu_{\bar{a}_j}, \vartheta_{\bar{a}_j} \right), & for\ C.C \end{cases} \tag{7}$$

Step 2: Calculate the criteria weights.

To successfully reduce the subjective randomness, the entropy ε_j with regard to C_j can be determined using the entropy measure given in Eq. (8).

$$\varepsilon_j = \frac{1}{m} \sum_{i=1}^{m} \frac{min\left(\mu_{\bar{a}_j}{}^{(q)}, \vartheta_{\bar{a}_j}{}^{(q)} \right) + \pi_{\bar{a}_j}{}^{(q)}}{max\left(\mu_{\bar{a}_j}{}^{(q)}, \vartheta_{\bar{a}_j}{}^{(q)} \right) + \pi_{\bar{a}_j}{}^{(q)}} \tag{8}$$

The criteria weights δ_j are calculated using Eq. (9)

$$\delta_j = \frac{1 - \varepsilon_j}{n - \sum_{j=1}^{n} \varepsilon_j} \tag{9}$$

where n indicates the number of attributes.

Step 3: Aggregated trapezoidal intuitionistic fuzzy decision matrix

Step 3.1: Find the IT-WAA-weighted arithmetic average operator on TrIFNs, calculated using Eq. (10)

given $x_{ij} = \bar{a}_j = \left([a_j, b_j, c_j, d_j]; \mu_{\bar{a}_j}, \vartheta_{\bar{a}_j} \right) (j = 1,2, \dots n))$,

$$\mu_{\bar{a}_j} = 1 - \prod_{j=1}^{n} \left(1 - \mu_{\bar{a}_j} \right)^{\delta_j}, \vartheta_{\bar{a}_j} = \prod_{j=1}^{n} \left(\vartheta_{\bar{a}_j} \right)^{\delta_j}, \ \pi_{\bar{a}_j} = 1 - \mu_{\bar{a}_j} - \vartheta_{\bar{a}_j} \tag{10}$$

Step 3.2: As seen in Eq. (11), all individual decision matrices can be combined to form an aggregated trapezoidal intuitionistic decision matrix.

$$D = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{11}$$

Step 4: Compute the weights of the DMs.

The trapezoidal intuitionistic fuzzy entropy e_q of the DMs' assessments is calculated using Eq. (12).

$$e_q \quad = \sum_{i=1}^{m}\sum_{j=1}^{n}\frac{min\left(\mu_{\bar{a}_j}{}^{(q)},\vartheta_{\bar{a}_j}{}^{(q)}\right)+\pi_{\bar{a}_j}{}^{(q)}}{max\left(\mu_{\bar{a}_j}{}^{(q)},\vartheta_{\bar{a}_j}{}^{(q)}\right)+\pi_{\bar{a}_j}{}^{(q)}} \tag{12}$$

the DMs' weights are denoted by
$\alpha_q\ (q = 1,2,\ldots l),\ 0 \le \alpha_q \le 1,\ \sum_{q=1}^{l}\alpha_q = 1$ is obtained using Eq. (13).

$$\alpha_q = \frac{1\text{-}e_q}{l\text{-}\sum_{q=1}^{l} e_q} \quad \text{, where l is the number of DMs.} \tag{13}$$

Step 5: Find the best and worst value.

The best value f_j^* and the worst value f_j^- for each attribute C_j are defined by Eq. (14).

$$f_j^* = \begin{cases} \max\limits_{i=1,2,\ldots m} f_{ij}, for\ benefit\ attribute\ \ C_j \\ \min\limits_{i=1,2,\ldots m} f_{ij}, for\ cost\ \ attribute\ \ C_j, \end{cases} \qquad j = (1,2,\ldots n) \tag{14}$$

$$f_j^- = \begin{cases} \min\limits_{i=1,2,\ldots m} f_{ij}, for\ benefit\ attribute\ \ C_j \\ \max\limits_{i=1,2,\ldots m} f_{ij}, for\ cost\ \ attribute\ \ C_j, \end{cases} \qquad j = (1,2,\ldots n)$$

Step 6: Compute the values $\boldsymbol{S_i}, \boldsymbol{R_i}, \boldsymbol{Q_i}$ using Eq. (15) & Eq. (16).

$S_i \rightarrow group\ utility\ value \quad R_i \rightarrow the\ individual\ regret\ value$
$Q_i \rightarrow the\ compromise\ value$

$$S_i = \sum_{j=1}^{n}\delta_j\left(\frac{d(f_j^+, f_{ij})}{d(f_j^+, f_j^-)}\right) \qquad R_i = \max_j \delta_j\left(\frac{d(f_j^+, f_{ij})}{d(f_j^+, f_j^-)}\right) \tag{15}$$

$$Q_i = \gamma\left(\frac{S_i - S^*}{S^- - S^*}\right) + (1-\gamma)\left(\frac{R_i - R^*}{R^- - R^*}\right) \tag{16}$$

where $S^- = max_i S_i,\quad S^* = min_i S_i,\quad R^- = max_i R_i,\quad R^* = min_i R_i,$
γ is the coefficient of decision mechanism. It can be chosen as

$$(\gamma > 0.5), \quad (\gamma = 0.5), \quad or\ (\gamma < 0.5)$$

Step 7: Rank the alternatives and derive the compromise solution.

Sort S_i, R_i, Q_i in the ascending order and generate three ranking lists $S_{[.]}, R_{[.]}, Q_{[.]}$. Then, the alternative $A^{(1)}$ that ranks the best in $Q_{[.]}$ (minimum value) and fulfills the following two conditions simultaneously would be the compromise solution.

Condition 1: (acceptable advantage).

$Q\left(A^{(a')}\right) - Q\left(A^{(a)}\right) \ge \frac{1}{m-1}$, where $A^{(a)}\ and\ A^{(a')}$ are the top two alternatives in Q_i.

Condition 2: (acceptable stability).

The alternative $A^{(a)}$ should be the best ranked by $S_i\ or/and\ R_i$.

If the above conditions cannot be satisfied simultaneously, there exist multiple compromise solutions.

i) Alternatives $A^{(a)}\ and\ A^{(a')}$ if only condition 2 is not satisfied.

ii)Alternatives $A^{(a)}, A^{(a\prime)}, \ldots, A^{(v)}$ if condition 1 is not satisfied, where $A^{(v)}$ is obtained based on the relation
$Q\left(A^{(v)}\right) - Q\left(A^{(a)}\right) < \frac{1}{m-1}\ for\ the\ maximum\ v$. (the positions of these alternatives are in closeness).

5. Incorporating the score and accuracy function to obtain the VIKOR index to rank the alternatives

Score component: (Weight x Score)

The "Score" component denotes a numerical evaluation of how well each alternative performed in relation to the criteria. The "Weight" element, which shows the relative value or priority given to the criteria, weighs this component. Here are some reasons the Score function is crucial:

- In a quantitative evaluation, the effectiveness of each alternative in relation to the decision criteria is quantified. Making decisions that are objectively based on facts rather than judgements is dependent on this.
- Reflects Criteria Importance: The formula recognises that some criteria are more important than others in the decision-making process by weighing the scores with the importance factors. As a result, decision outcomes can be tailored to the decision-maker's particular priorities.

Accuracy component: ((1 - Weight) Accuracy)

The "Accuracy" component indicates how close each potential solution is to the best (ideal) option. The complement of the Weight factor is used to weight it. Here are some reasons the Accuracy function is crucial:

i. Accuracy aids in determining how closely a substitute comes to the ideal answer when all factors are taken into account. This reflects how much of a compromise or trade-off might be required while making a decision.
ii. Objective Balancing: In many real-world situations, decision-makers must choose between competing requirements. By measuring and addressing these trade-offs, the Accuracy function makes it feasible to find alternatives that offer the best compromise between conflicting objectives.

A comprehensive decision-making tool that takes into account both the quantitative performance of alternatives and their near to the ideal answer is essentially provided by the proposed **VIKOR Index formula**, which combines the Score and Accuracy functions. It is crucial to strike this balance between the compromise element (Accuracy) and the concrete data (Score) because it enables decision-makers to make well-informed decisions that are in line with their priorities while also taking into account the trade-offs entailed in multicriteria decision-making. The VIKOR method's capacity to capture the decision-maker's preferences and goals is further improved by the Weight factor, which guarantees that criteria are weighted according to their importance.

5.1. Advantages of incorporating the score and accuracy function to obtain the VIKOR index to rank the alternatives

The VIKOR approach is employed in MCDM to assist in decision-making when numerous competing criteria must be taken into account. The goal of VIKOR is to find a middle ground between these competing demands. This technique can benefit from the addition of score and accuracy function values in a number of ways.

i) Comprehensive evaluation: By utilizing both the quantitative and qualitative aspects of the decision problem by using the values for both the accuracy and score function, a more thorough assessment of the potential solutions can be achieved.

ii) Balancing objectives: Score functions provide numerical indicators of how well each alternative performs concerning each criterion, whereas accuracy functions reveal how closely each alternative approaches the ideal and anti-ideal solutions. By considering both, a balance can be struck between the objective (score-based) and subjective (accuracy-based) elements of the decision-making process.

iii) Robustness and sensitivity: By including accuracy functions, the sensitivity of results to modifications in the evaluation process is taken into account. It takes variations in decision data into account and aids in determining the stability of the ranking of options in the face of potential fluctuations.

iv) Handling uncertainty: Accuracy functions can take into account data imprecision and uncertainty, which can be helpful in instances where there may be scant or ambiguous information on specific criteria.

Construct the weighted arithmetic average operator
$TrIFN - WAA_{\delta}(\bar{a}_1, \bar{a}_2, \dots \bar{a}_n) = \sum_{j=1}^{n} \delta_j \bar{a}_j$ of the TrIFNs represented by the Table (7).

Hence, calculate the score and accuracy values as outlined in Table 9. The score's objective is to quantify and represent the performance or quality of each alternative on a standardized scale, making it easier to compare and evaluate them. The score function values can be determined using Eq. (4). On the other hand, the accuracy function takes into consideration the inherent fuzziness and imprecision involved within the evaluation process to determine how closely each platform aligns with the optimal answer. You can calculate the accuracy function values using Eq. (5). Finally, compute the VIKOR index using Eq. (17).

VIKOR index = (Weight × Score) + ((1 - Weight) × Accuracy) (17)

6. Numerical Example

The proposed approach is applied to a practical decision-making problem involving the ranking of metaverse platforms. This problem is broken down into two subsections: first, problem definition, and second, the computation process. Finally, the discussion of the results is presented.

6.1. Problem Definition

By providing an appropriate example involving the selection of a metaverse platform while taking into account subjective factors and homogeneous GDM, the proposed method is demonstrated.

In this example, a committee comprising four rational DMs well-versed in the subject matter is constituted, identified as DM1, DM2, DM3, and DM4. The committee collectively agrees to take into account a set of six criteria. Four metaverse platforms, namely, A1, A2, A3, and A4, were selected for further analysis. The suggested MCDM algorithm was used to rank, evaluate, and choose the best metaverse platforms that are being taken into consideration. In the following subsection, a demonstration of the developed and suggested paradigm demonstrates the process for addressing the metaverse platform selection problem. The six criteria are described in Table 1.

Table 1
Criteria for decision-making

Code	Criteria	Remarks
C1	User Experience (UE)	Focuses on the intuitiveness, usability, and overall satisfaction of users interacting with the metaverse platform's interface. (Beneficial Criteria)
C2	Features and Functionality (FF)	Considers the range and quality of features, tools, and capabilities offered by the platform to meet user requirements and enable diverse use cases. (Beneficial Criteria)
C3	Performance (PE)	Evaluates the speed, responsiveness, and efficiency of the platform in delivering a smooth and lag-free experience to users. (Beneficial Criteria)
C4	Security (SE)	Assesses the measures and protocols implemented by the platform to safeguard user data, protect against unauthorized access, and ensure privacy and confidentiality. (Non-Beneficial Criteria)
C5	Community Support (CS)	Examines the availability of active and engaged communities, forums, and resources that provide assistance, guidance, and collaboration opportunities for platform users. (Beneficial Criteria)
C6	Scalability (SC)	Considers the platform's ability to handle increased user load, data volume, and transactional demands without compromising performance or functionality as the user base and activity grow. (Beneficial Criteria)

6.2. Calculations and Discussions

There are four possible metaverse platforms, six criteria, and four DMs in the current decision-making challenge. All criteria are arbitrary, ambiguous, and subject to interpretation. Therefore, the DMs estimate the corresponding performance rating of the alternative platforms using language variables. For the purpose of estimating performance ratings, six degrees of linguistic variables—excellent, good, average, poor, minimal, and neutral—were used. Each language variable was quantified using a unique TrIFN. The language terms, acronyms, and matching TrIFNs for performance rating are presented in Table 2.

Table 2
Trapezoidal intuitionistic fuzzy representation of linguistics descriptors of the ratings of the criteria

Linguistic variables	TrIFNs
Excellent (E)	([6,7,8,9]; 08.,0.1)
Good (G)	([5,6,7,8];0.8,0.2)
Average (A)	([4,6,7,8];0.6,0.3)
Poor (P)	([3,4,5,7]; 0.6,0.3)
Minimal (M)	([1,2,3,4];0.7,0.3)
Neutral (N)	([2,3,4,5];0.6,0.3)

Step 1. Four decision-makers evaluated four different metaverse platforms using the required six degrees of linguistic variables, which are viewed as the alternatives' performance evaluations. Table 3 displays the choice matrix with performance ratings in relation to linguistic variables**.**

Table 3
Assessment information: Rating of the alternatives by DMs

Attributes	DM1				DM2				DM3				DM4			
	A1	**A2**	**A3**	**A4**	**A1**	**A2**	**A3**	**A4**	**A1**	**A2**	**A3**	**A4**	**A1**	**A2**	**A3**	**A4**
C1	M	N	A	G	G	N	A	P	P	G	E	N	E	M	A	G
C2	G	E	A	N	P	M	A	N	A	P	G	N	N	G	P	E
C3	P	G	A	E	E	M	P	G	A	P	G	N	E	N	G	M
C4	A	G	N	E	M	P	M	N	A	G	G	E	G	P	A	M
C5	G	E	A	N	G	A	E	P	P	E	P	G	P	N	G	E
C6	P	A	E	G	P	E	M	N	N	E	P	G	N	P	E	M

The initial (aggregated) decision-making matrix corresponding to the rating of the alternatives by DMs is shown in Table 4.

Table 4
Initial decision-making matrix

DM		C1	C2	C3
DM1	A1	([1,2,3,4];0.7,0.3)	([1,2,3,4];0.7,0.3)	([3,4,5,7];0.6,0.3)
	A2	([2,3,4,5];0.6,0.3)	([6,7,8,9];0.8.,0.1)	([5,6,7,8];0.8,0.2)
	A3	([4,6,7,8];0.6,0.3)	([4,6,7,8];0.6,0.3)	([4,6,7,8];0.6,0.3)
	A4	([5,6,7,8];0.8,0.2)	([2,3,4,5];0.6,0.3)	([6,7,8,9];0.8.,0.1)
		C4	C5	C6
DM1	A1	([4,6,7,8];0.6,0.3)	([5,6,7,8];0.8,0.2)	([3,4,5,7];0.6,0.3)
	A2	([5,6,7,8] ;0.8,0.2)	([6,7,8,9]; 08.,0.1)	([4,6,7,8];0.6,0.3)
	A3	([2,3,4,5];0.6,0.3)	([4,6,7,8];0.6,0.3)	([6,7,8,9];0.8,0.1)
	A4	([6,7,8,9]; 08.,0.1)	([2,3,4,5];0.6,0.3)	([5,6,7,8];0.8,0.2)
		C1	C2	C3
DM2	A1	([5,6,7,8];0.8,0.2)	([3,4,5,7];0.6,0.3)	([6,7,8,9];0.8,0.1)
	A2	([2,3,4,5];0.6,0.3)	([1,2,3,4];0.7,0.3)	([1,2,3,4];0.7,0.3)
	A3	([4,6,7,8];0.6,0.3)	([4,6,7,8];0.6,0.3)	([3,4,5,7];0.6,0.3)
	A4	([3,4,5,7];0.6,0.3)	([2,3,4,5];0.6,0.3)	([5,6,7,8];0.8,0.2)
		C4	C5	C6
DM2	A1	([1,2,3,4];0.7,0.3)	([5,6,7,8];0.8,0.2)	([3,4,5,7]; 0.6,0.3)
	A2	([3,4,5,7];0.6,0.3)	([4,6,7,8];0.6,0.3)	([6,7,8,9];0.8.,0.1)
	A3	([1,2,3,4];0.7,0.3)	([6,7,8,9];0.8.,0.1)	([1,2,3,4];0.7,0.3)
	A4	([2,3,4,5];0.6,0.3)	([3,4,5,7];0.6,0.3)	([2,3,4,5];0.6,0.3)
		C1	C2	C3
DM3	A1	([3,4,5,7];0.6,0.3)	([4,6,7,8];0.6,0.3)	([4,6,7,8];0.6,0.3)
	A2	([5,6,7,8];0.8,0.1)	([3,4,5,7];0.6,0.3)	([3,4,5,7];0.6,0.3)
	A3	([6,7,8,9];0.8,0.1)	([5,6,7,8];0.8,0.2)	([5,6,7,8];0.8,0.2)
	A4	([2,3,4,5];0.6,0.3)	([2,3,4,5];0.6,0.3)	([2,3,4,5];0.6,0.3)
		C4	C5	C6
DM3	A1	([4,6,7,8];0.6,0.3)	([3,4,5,7];0.6,0.3)	([2,3,4,5];0.6,0.3)
	A2	([5,6,7,8];0.8,0.2)	([6,7,8,9];0.8.,0.1)	([6,7,8,9];0.8.,0.1)
	A3	([5,6,7,8];0.8,0.2)	([3,4,5,7];0.6,0.3)	([3,4,5,7];0.6,0.3)
	A4	([6,7,8,9];0.8.,0.1)	([5,6,7,8];0.8,0.2)	([5,6,7,8];0.8,0.2)
		C1	C2	C3
DM4	A1	([6,7,8,9];0.8,0.1)	([2,3,4,5];0.6,0.3)	([6,7,8,9];0.8.,0.1)
	A2	([1,2,3,4];0.7,0.3)	([5,6,7,8];0.8,0.2)	([2,3,4,5];0.6,0.3)
	A3	([4,6,7,8];0.6,0.3)	([3,4,5,7];0.6,0.3)	([5,6,7,8];0.8,0.2)
	A4	([6,7,8,9];0.8.,0.1)	([6,7,8,9];08.,0.1)	([1,2,3,4];0.7,0.3)
		C4	C5	C6
DM4	A1	([5,6,7,8];0.8,0.2)	([3,4,5,7]; 0.6,0.3)	([2,3,4,5];0.6,0.3)
	A2	([3,4,5,7];0.6,0.3)	([2,3,4,5];0.6,0.3)	([3,4,5,7];0.6,0.3)

DM		C1	C2	C3
	A3	([4,6,7,8];0.6,0.3)	([5,6,7,8];0.8,0.2)	([6,7,8,9];0.8,0.1)
	A4	([1,2,3,4];0.7,0.3)	([6,7,8,9];0.8.,0.1)	([1,2,3,4];0.7,0.3)

Table 5 represents the normalized decision matrix, which is framed using Eq. (7).

Table 5
Normalized decision matrix

DM		C1	C2	C3
DM1	A1	([0.25,0.5,0.75,1];0.7,0.3)	([0.63,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0714,1];0.7,0.3)
	A2	([0.4,0.6,0.8,1];0.6,0.3)	([0.67,0.79,0.89,1];0.8,0.1)	([0.63,0.75,0.88,1];0.8,0.2)
	A3	([0.5,0.75,0.88,1];0.7,0.3)	([0.5,0.75,0.88,1];0.6,0.3)	([0.50,0.75,0.88,1];0.8,0.2)
	A4	([0.63,0.75,0.88,1];0.8,0.2)	([0.4,0.6,0.8,1];0.6,0.3)	([0.67,0.79,0.89,1];0.7,0.2)
		C4	C5	C6
DM1	A1	(0.5,0.75,0.88,1];0.5,0.5)	([0.63,0.75,0.88,1];0.8,0.2)	([0.43,0.57,0.71,1];0.6,0.3)
	A2	([0.63,0.75,0.88,1];0.8,0.2)	([.67,0.79,0.89,1];0.6,0.3)	([05,0.75,088,1];0.5,0.5)
	A3	([0.4,0.6,0.8,1];0.8,0.2)	([0.5,0.76,0.8,1];0.6,0.3)	([0.67,0.78,0.89,1];0.6,0.3)
	A4	([0.67,0.78,0.89,1];0.8,0.2)	([0.40,0.60,0.80,1];0.6,0.2)	([0625,0.75,0.88,1];0.7,0.3)
		C1	C2	C3
DM2	A1	([0.63,0.75,088,1];0.7,0.3)	([0.43,0.57,0.71,1];0.6,0.3)	([0.68,0.78,0.89,1];0.6,0.3)
	A2	([0.40,0.60,0.80,1];0.6,0.3)	([0.25,0.50,0.75,1];0.8,0.2)	([0.25,0.50,0.75,1];0.7,0.3)
	A3	([0.50,0.75,0.88,1];0.8,0.2)	([0.50,0.75,0.88,1];0.6,0.3)	([0.43,057,0.71,1];0.5,0.5)
	A4	([043,0.57,0.71,1];0.6,0.3)	([0.40,0.60,0.80,1];0.8,0.2)	([0.63,0.75,0.88,1];0.8,0.2)
		C4	C5	C6
DM2	A1	([0.25,0.50,0.75,1];0.7,0.3)	([0.63,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0.71,1];0.7,0.3)
	A2	([0.43,0.57,0.71,1];0.6,0.3)	([0.50,0.75,0.88,1];0.7,0.3)	([0.67,0.79,0.89,1];0.8,0.2)
	A3	([0.25,0.50,0.75,1];06,0.4)	([0.67,0.78,0.89,1];0.8,0.1)	([0.25,0.50,0.75,1];0.8,0.1)
	A4	([0.4,0.60,0.80,1];0.7,0.3)	([0.43,0.57,071,1];0.6,0.2)	([0.40,0.60,0.80,1]0.8,0.2)
		C1	C2	C3
DM3	A1	([0.43,057,0.71,1];0.6,0.3)	([0.50,0.75,0.88,1];0.8,0.2)	([0.50,0.75,0.88,1];0.8,0.1)
	A2	([0.63,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0.71,1];0.6,0.3)	([0.43,0.57,0.71,1];0.6,0.3)
	A3	([0.68,0.79,0.89,1];0.6,0.3)	([0.63,0.75,0.88,1];0.8,0.2)	([0.63,0.75,0.88,1];0.7,0.3)
	A4	([0.4,0.60,0.80,1];0.6,0.2)	([0.40,0.60,0.80,1];0.7,0.3)	([0.40,0.60,0.80,1];0.6,0.4)
		C4	C5	C6
DM3	A1	([0.5,0.75,0.88,1];0.8,0.2)	([0.43,0.57,0.71,1];0.6,0.3)	([0.4,0.60,0.80,1];0.6,0.3)
	A2	([0.63,0.75,0.88,1];0.8,0.2)	([0.67,0.79,0.89,1];0.7,0.3)	([0.68,0.79,0.89,1];0.6,0.3)
	A3	([0.5,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0.71,1];0.6,0.3)	([0.43,0.57,0.71,1];0.6,0.3)
	A4	([0.67,0.78,0.89,1];0.6,0.3)	([0.63,0.75,0.88,1];0.8,0.2)	([0.63,0.75,0.88,1];0.7,0.3)
		C1	C2	C3
DM4	A1	([0.67,0.78,0.89,1];0.7,0.3)	([0.40,0.60,0.80,1];0.7,0.3)	([0.67,0.78,0.89,1];0.7,0.3)
	A2	([0.25,0.50,0.75,1];06,0.3)	([0.63,0.75,0.88,1];0.6,0.3)	([0.40,0.60,0.80,1];0.6,0.3)
	A3	([0.50,0.75,0.88,1];0.8,0.2)	([0.43,0.57,0.71,1];0.7,0.3)	([0.63,0.75,0.88,1];0.7,0.3)
	A4	([0.63,0.75,0.88,1];0.7,0.3)	([0.67,0.79,0.89,1];0.6,0.3)	([0.25,0.50,0.75,1];0.6,0.3)
		C4	C5	C6
DM4	A1	([0.63,0.75,0.88,1];0.7,0.2)	([0.43,0.57,0.71,1];0.5,0.3)	([0.40,0.60,0.80,1];0.7,0.3)
	A2	([0.43,0.57,0.71,1];0.6,0.3)	([0.40,0.60,0.80,1];0.8,0.2)	([0.43,0.57,0.71,1];0.8,0.2)
	A3	([0.50,0.75,0.88,1];0.8,0.2)	([0.63,0.75,0.88,1];0.8,0.2)	([0.67,0.78,0.89,1];0.6,0.3)
	A4	([0.25,0.50,0.75,1];0.7,0.3)	([0.67,0.79,0.89,1];0.7,0.3)	[0.25,0.50,0.75,1];0.8,0.2)

Step 2: The entropy ε_j with regard to C_j is calculated using Eq. (8)
$\varepsilon_1 = 1.718254;\ \ \varepsilon_2 = 1.834325;\ \ \varepsilon_3 = 1.630952; \varepsilon_4 = 1.675595;\ \ \varepsilon_5 = 1.615079;\ \varepsilon_6 = 1.704365$
and the criteria weights δ_j are calculated using Eq (9).
$\delta_1 = 0.17189\ ; \delta_2 = 0.19967; \delta_3 = 0.15100; \delta_4 = 0.16168;\quad \delta_5 = 0.14720; \delta_6 = 0.16857$

Step 3: Aggregated trapezoidal intuitionistic fuzzy decision matrix is framed by first finding the IT-WAA-weighted arithmetic average operator on TrIFNs, which is calculated using Eq. (10), as shown in Table 6.

Table 6
IT-WAA-weighted arithmetic average operator on TrIFNs

DM		C1	C2	C3
DM1	A1	([0.25,0.5,0.75,1];0.7,0.3)	([0.63,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0714,1];0.7,0.3)
	A2	([0.4,0.6,0.8,1];0.6,0.3)	([0.67,0.79,0.89,1];0.8,0.1)	([0.63,0.75,0.88,1];0.8,0.2)
	A3	([0.5,0.75,0.88,1];0.7,0.3)	([0.5,0.75,0.88,1];0.6,0.3)	([0.50,0.75,0.88,1];0.8,0.2)
	A4	([0.63,0.75,0.88,1];0.8,0.2)	([0.4,0.6,0.8,1];0.6,0.3)	([0.67,0.79,0.89,1];0.7,0.2)
		C4	C5	C6
DM1	A1	(0.5,0.75,0.88,1];0.5,0.5)	([0.63,0.75,0.88,1];0.8,0.2)	([0.43,0.57,0.71,1];0.6,0.3)
	A2	([0.63,0.75,0.88,1];0.8,0.2)	([.67,0.79,0.89,1];0.6,0.3)	([05,0.75,088,1];0.5,0.5)
	A3	([0.4,0.6,0.8,1];0.8,0.2)	([0.5,0.76,0.8,1];0.6,0.3)	([0.67,0.78,0.89,1];0.6,0.3)
	A4	([0.67,0.78,0.89,1];0.8,0.2)	([0.40,0.60,0.80,1];0.6,0.2)	([0625,0.75,0.88,1];0.7,0.3)
		C1	C2	C3
DM2	A1	([0.63,0.75,088,1];0.7,0.3)	([0.43,0.57,0.71,1];0.6,0.3)	([0.68,0.78,0.89,1];0.6,0.3)
	A2	([0.40,0.60,0.80,1];0.6,0.3)	([0.25,0.50,0.75,1];0.8,0.2)	([0.25,0.50,0.75,1];0.7,0.3)
	A3	([0.50,0.75,0.88,1];0.8,0.2)	([0.50,0.75,0.88,1];0.6,0.3)	([0.43,057,0.71,1];0.5,0.5)
	A4	([043,0.57,0.71,1];0.6,0.3)	([0.40,0.60,0.80,1];0.8,0.2)	([0.63,0.75,0.88,1];0.8,0.2)
		C4	C5	C6
DM2	A1	([0.25,0.50,0.75,1];0.7,0.3)	([0.63,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0.71,1];0.7,0.3)
	A2	([0.43,0.57,0.71,1];0.6,0.3)	([0.50,0.75,0.88,1];0.7,0.3)	([0.67,0.79,0.89,1];0.8,0.2)
	A3	([0.25,0.50,0.75,1];06,0.4)	([0.67,0.78,0.89,1];0.8,0.1)	([0.25,0.50,0.75,1];0.8,0.1)
	A4	([0.4,0.60,0.80,1];0.7,0.3)	([0.43,0.57,071,1];0.6,0.2)	([0.40,0.60,0.80,1]0.8,0.2)
		C1	C2	C3
DM3	A1	([0.43,057,0.71,1];0.6,0.3)	([0.50,0.75,0.88,1];0.8,0.2)	([0.50,0.75,0.88,1];0.8,0.1)
	A2	([0.63,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0.71,1];0.6,0.3)	([0.43,0.57,0.71,1];0.6,0.3)
	A3	([0.68,0.79,0.89,1];0.6,0.3)	([0.63,0.75,0.88,1];0.8,0.2)	([0.63,0.75,0.88,1];0.7,0.3)
	A4	([0.4,0.60,0.80,1];0.6,0.2)	([0.40,0.60,0.80,1];0.7,0.3)	([0.40,0.60,0.80,1];0.6,0.4)
		C4	C5	C6
DM3	A1	([0.5,0.75,0.88,1];0.8,0.2)	([0.43,0.57,0.71,1];0.6,0.3)	([0.4,0.60,0.80,1];0.6,0.3)
	A2	([0.63,0.75,0.88,1];0.8,0.2)	([0.67,0.79,0.89,1];0.7,0.3)	([0.68,0.79,0.89,1];0.6,0.3)
	A3	([0.5,0.75,0.88,1];0.7,0.3)	([0.43,0.57,0.71,1];0.6,0.3)	([0.43,0.57,0.71,1];0.6,0.3)
	A4	([0.67,0.78,0.89,1];0.6,0.3)	([0.63,0.75,0.88,1];0.8,0.2)	([0.63,0.75,0.88,1];0.7,0.3)
		C1	C2	C3
DM4	A1	([0.67,0.78,0.89,1];0.7,0.3)	([0.40,0.60,0.80,1];0.7,0.3)	([0.67,0.78,0.89,1];0.7,0.3)
	A2	([0.25,0.50,0.75,1];06,0.3)	([0.63,0.75,0.88,1];0.6,0.3)	([0.40,0.60,0.80,1];0.6,0.3)
	A3	([0.50,0.75,0.88,1];0.8,0.2)	([0.43,0.57,0.71,1];0.7,0.3)	([0.63,0.75,0.88,1];0.7,0.3)
	A4	([0.63,0.75,0.88,1];0.7,0.3)	([0.67,0.79,0.89,1];0.6,0.3)	([0.25,0.50,0.75,1];0.6,0.3)
		C4	C5	C6
DM4	A1	([0.63,0.75,0.88,1];0.7,0.2)	([0.43,0.57,0.71,1];0.5,0.3)	([0.40,0.60,0.80,1];0.7,0.3)
	A2	([0.43,0.57,0.71,1];0.6,0.3)	([0.40,0.60,0.80,1];0.8,0.2)	([0.43,0.57,0.71,1];0.8,0.2)
	A3	([0.50,0.75,0.88,1];0.8,0.2)	([0.63,0.75,0.88,1];0.8,0.2)	([0.67,0.78,0.89,1];0.6,0.3)

Second, the aggregated trapezoidal intuitionistic fuzzy decision matrix D given by Eq. (11) is represented in Table 7.

Table 7
Aggregated trapezoidal intuitionistic fuzzy decision matrix D

C1	C2	C3
([0.489,0.647,0.805,1]; 0.221,0.525])	([0.490,0.670,0.817,1]; 0.267,0.720])	([0.563,0.718,0.841,1]; 0.267,0.688])
([0.421,0.614,0.807,1]; 0.196,0.497])	([0.493,0.650,0.807,1]; 0.271,0.672])	([0.428,0.606,0.785,1]; 0.253,0.721])
([0.543,0.757,0.879,1]; 0.233,0.513])	([0.515,0.707,0.836,1]; 0.253,0.720])	([0.545,0.706,0.835,1]; 0257,0.710])
([0.519,0.668,0.816,1]; 0.231,0.466])	([0.464,0.643,0.821,1]; 0.252,0.703])	([0.487,0.658,0.829,1]; 0.252,0.716])
C4	**C5**	**C6**
([0.469,0.688,0.844,1]; 0.255,0])	([0.527,0.661,0.795,1]; 0.24,0.721])	([0.414,0.586,0.757,1]; 0.232,0.740])
([0.529,0.663,0.797,1]; 0.274,0])	([0.561,0.728,0.864,1]; 0.26, 0.723])	([0.567,0.721,0.843,1]; 0.25,0])
([0.445,0.650,0.825,1]; 0.282,0])	([0.553,0.711,0.837,1];0 .27,0])	(0.503,0.656,0.810,1]; 0.238,0.692])
([0.500,0.667,0.833,1]; 0.266,0.72])	([0.529,0.674,0.820,1]; 0.5,0.685])	([0.479,0.653,0.826,1]; 0.295,0.705])

Step 4: Compute the weights of the DMs.

The trapezoidal intuitionistic fuzzy entropy e_q of the DMs' assessments is calculated using Eq. (12).

$e_1 = 10.8909$; $e_2 = 10.5397$; $e_3 = 10.9246$; $e_4 = 10.3464$

Compute the weights of the DMs α_q using Eq. (13)

$\alpha_1 = 0.2556$; $\alpha_2 = 0.2465$; $\alpha_3 = 0.2564$; $\alpha_4 = 0.2415$

Step 5: The best value f_j^* and the worst value f_j^- for each attribute C_j are defined by Eq. (14), and the values are shown in Table 8.

Table 8
The best and worst values

$Best\ value\ f_j^*$	$worst\ value\ f_j^-$
f_1^* = ([0.54,0.76,0.88,1];0.23,0.51)	f_1^- = ([0.42,0.61,0.82,1]; 0.20,0.50)
f_2^* = ([0.52,0.71,0.84,1]; 0.25,0.72)	f_2^- = ([0.47,0.64,0.82,1]; 0.25,0.70)
f_3^* = ([0.56,0.72,0.84,1]; 0.27,0.69)	f_3^- = ([0.43,0.61,0.79,1]; 0.25,0.72)
f_4^* = ([0.53,0.66,0.78,1]; 0.27,0)	f_4^- = ([0.45,0.65,0.83,1]; 0.28,0)
f_5^* = ([0.57,0.73,0.86,1]; 0.26,0.72)	f_5^- = ([0.53,0.66,0.80,1]; 0.24,0.72)
f_6^* = ([0.57,0.72,0.84,1]; 0.26,0)	f_6^- = ([0.41,0.59,0.76,1]; 0.23,0.74)

Step 6: Both the group utility value $\boldsymbol{S_i}$ and the individual regret value $\boldsymbol{R_i}$ are calculated using Eq. (15), where $d\left(f_j^+,\ f_{ij}\right)$ & $d\ (f_j^+,\ \ f_j^-)$ are obtained using Eq. (2).

The compromise value $\boldsymbol{Q_i}$ is calculated using Eq. (16). The values of $\boldsymbol{S_i}, \boldsymbol{R_i}, \boldsymbol{Q_i}$ are given in Table 9.

Table 9
The values of S_i, R_i, Q_i

S_i	R_i	Q_i
$S_1 = 0.6456$	$R_1 = 0.4564$	$Q_1 = 0.0496$
$S_1 = 0.6456$	$R_1 = 0.4564$	$Q_1 = 0.0496$
$S_1 = 0.6456$	$R_1 = 0.4564$	$Q_1 = 0.0496$

Step 7: To obtain the compromise solution, the values of S_i, R_i, Q_i are arranged in the ascending order, and three ranking lists $S_{[.]}, R_{[.]}, Q_{[.]}$ are generated, as given in Table 10.

Table 10
Three ranking lists $S_{[.]}, R_{[.]}, Q_{[.]}$

$S_{[.]}$	$R_{[.]}$	$Q_{[.]}$	Alternatives	Ranking
0.2228	0.4564	0.0070	A2	I
0.6456	0.4931	0.0496	A1	II
3.4269	2.3224	0.7331	A3	III
4.4870	3.0666	1.0000	A4	IV

The minimum value in the list $Q_{[.]}$ is alternative A2 (Platform B), and the next minimum value corresponds to alternative A1 (platform A).
Condition 1: (acceptable advantage)

$$\mathrm{Q}(\mathrm{A1}) - \mathrm{Q}(\mathrm{A2}) = 0.0496 - 0.0070 \ngeq \frac{1}{4-1}$$

Condition 2:(acceptable stability)
Alternative A2 (Platform B) is also best ranked by S_i

Since the above two conditions are not satisfied simultaneously, there exist multiple compromise solutions.

Alternatives A2 and A1 are the compromise solutions, since condition 1 is not satisfied but $\mathrm{Q}(\mathrm{A1}) - \mathrm{Q}(\mathrm{A2}) = 0.0496 - 0.0070 < \frac{1}{4-1}$.

The alternative A2 (platform B) and alternative A1 (platform A) are in closeness in ranking.

$\boldsymbol{A2 > A1 > A3 > A4}$ **A2 (platform B) is the best alternative**

The score function values are found using Eq. (4). The accuracy function takes into account the inherent fuzziness and imprecision involved in the evaluation process to determine how close each platform is to the optimal answer. The accuracy function values are found using Eq (5), as shown in Table 11.

Table 11
Score and accuracy function values

	TrIFN	Expected value $\mathrm{I}(\tilde{a})$	Score function $\mathrm{S}(\tilde{a})$	Accuracy function $H(\widetilde{a})$
$\tilde{a}_1$	([0.4901,0.6607,0.8096,1];0.2479,0)	0.4618	0.1145	0.114505
$\tilde{a}_2$	([0.4991,0.6627,0.8164,1];0.2414,0)	0.4621	0.1116	0.111557
$\tilde{a}_3$	([0.5164,0.6983,0.8373,1];0.2549,0)	0.4787	0.1220	0.122012
$\tilde{a}_4$	([0.4950,0.6596,0.8242,1];0.2582,0.6573)	0.2238	-0.0893	0.20487

The score and accuracy function are incorporated to obtain the VIKOR index using Eq (17) to rank the alternatives, as shown in Table 12.

VIKOR Index = (Weight × Score) + ((1 - Weight) × Accuracy)

For simplicity, let's assume that the weight for score is 0.6 and the weight for accuracy is 0.4. The alternative with the lowest VIKOR index represents the best compromise solution.

Table 12
Ranking based on the VIKOR index

Alternatives	VIKOR index	Ranking based on VIKOR index
A1	0.045802	II
A2	0.044623	I
A3	0.048805	III
A4	0.081948	IV

The ranking orders of alternatives A1, A2, A3, A4 are platform B, platform A, platform C, and finally platform D**.**

$A_2 > A_1 > A_3 > A_4$. **A2 (platform B) is the best alternative**

The comparison of rankings of alternatives using the TrIF VIKOR method and the VIKOR index is represented by Table 13.

Table 13
Comparison of rankings of alternatives

Alternatives	VIKOR MCDM Q[.]	VIKOR Index
A1	II	II
A2	I	I
A3	III	III
A4	IV	IV

The correlation analysis between the TrIF VIKOR method and the VIKOR Index incorporating the score and accuracy function is shown in Table 14. There is a positive correlation between the TrIF VIKOR ranking and the ranking of alternatives using the VIKOR index obtained by incorporating the score and accuracy function.

Table 14
Correlation between the ranking methods

Correlation Between		Correlation coefficient
VIKOR MCDM Q[.]	VIKOR INDEX values	0.801051

7. Validation of results

The purpose of this comparison study is to assess and compare the outcomes of multi-criteria decision-making using the suggested VIKOR index with those attained using other recognized approaches. The main objective is to present a thorough examination of the proposed VIKOR Index method's applicability, as well as a comparison with other commonly used techniques. The Spearman's correlation coefficient is found to validate the results found.

7.1. Comparison of the results obtained using the proposed VIKOR index with those obtained using other methods

In this section, a comparison is made between the results obtained using the VIKOR index technique and those obtained using the widely accepted MCDM method. To ensure a fair comparison, the input results of our proposed method are defined in terms of TrIFNs. A similar fuzzification process as traditional MCDM approaches was conducted. Additionally, the techniques commonly used in contemporary research are chosen. The ranking of alternatives by different MCDM methods is presented in Figure 2.

Figure 2 demonstrates how comparable the ranks of alternatives derived using different techniques are. In this case, nearly all of the techniques concur on their ranking for both the top- (A2) and the lowest-ranked alternative (A4). The results were confirmed by using Spearman's correlation coefficient (SCC), although the deviations were not significant. The SCC values are calculated using Eq (18).

$$SCC = 1 - \frac{6\sum_{i=1}^{n} d_i^2}{n(n^2-1)} \quad (18)$$

where d_i shows the discrepancy between a given element's rank in the vector ω and that element's rank in the reference vector, and n shows the total number of ranked elements. SCC value of 1 (the "ideal positive correlation") is determined by identical ranks of the components. SCC value of -1 indicates that the ranks are perfectly incongruent ("ideal negative correlation"), and SCC value of 0 indicates no correlation between the ranks. The SCC values are given in Table 15.

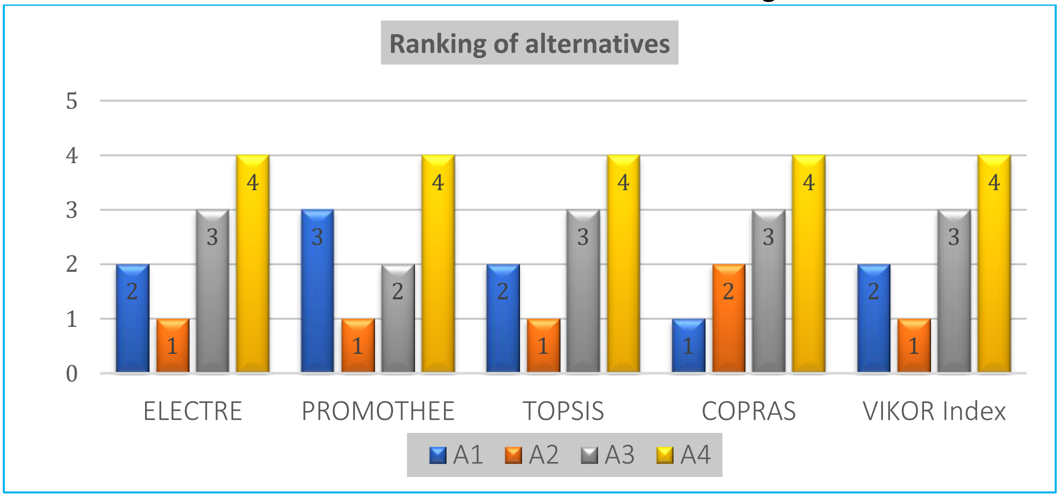

Fig. 2. Rank of alternatives by applying different MCDM methods

Table 15
SCC values for alternative ranks obtained using different MCDM methods

	ELECTRE	PROMOTHEE	TOPSIS	COPRAS	VIKOR INDEX
ELECTRE	1	0.8	1	0.2	0.4
PROMOTHEE		1	0.8	0.4	0.8
TOPSIS			1	0.2	0.4
COPRAS				1	0.8
VIKOR INDEX					1

Table 15 shows that the SCC values are positively correlated between the different MCDM methods. This indicates that the VIKOR index method's findings are satisfactory and that the method is resilient.

7.2. Sensitivity Analysis

Sensitivity analysis can be used to make judgements using all the information needed for the decision model to function properly. It helps decision analysts understand the risks, advantages, and disadvantages related to the limitations and domain of a decision model. Almost all decisions are made in the presence of uncertainty. When making decisions based on numerous parameter approximations, sensitivity analysis becomes the optimal approach. A sensitivity analysis can be used to establish a conclusion after all the uncertain parameters have been substituted with their predicted values. Sensitivity analysis proves to be a valuable technique that helps decision-makers in more than just arriving at a solution to a problem. The purpose of the sensitivity analysis is to look at how the shifting conditions affect the ranking result's stability. In this study,[43] have done several experiments with different parameter values (i.e., α, β, δ, and k) to track the ranking outcomes. The analysts are particularly interested in the stability of the outcome obtained through the use of MCDM models. When the specified conditions change, the stability is broken. A multi-phased sensitivity analysis is carried out [22]and conclude that by altering two fundamental circumstances, LOPCCSA produces a remarkably stable result, as seen by its performance via sensitivity analysis. This work [44] highlights global patterns and offers a strategy for using sensitivity analysis in MCDM research, shedding light on trends in scientific advancements and collaborations. Knowledge on the state of sensitivity analysis research at the moment can be useful to researchers in the whole MCDM field.

In this study, a sensitivity analysis was conducted for the VIKOR Index, specifically focusing on the weights, as shown in Table 16. The weights were varied between 0.1 to 1 and VIKOR Index found and ranking of alternatives found. This analysis confirmed that alternative A2 (platform B) is the best metaverse platform, in all the cases. A sensitivity analysis of the VIKOR Index, concentrating on changing the weights within the specified range (0.1 to 1), has yielded important information about the stability and robustness of the decision-making process. Throughout all weight situations, option A2 (platform B) continuously ranked as the best metaverse platform, according to the study.

Table 16
Sensitivity analysis -VIKOR index

wt	score value	weight*score value	accuracy value	(1-wt)	(1-wt)* accuracy value	VIKOR index	Ranking	Alternatives
0.1	-0.0000000017	-0.0000000002	0.1145053639	0.9	0.1031	0.1031	II	A1
0.1	0.0000000000	0.0000000000	0.1115565387	0.9	0.1004	0.1004	I	A2
0.1	-0.0000000005	-0.0000000001	0.1220115125	0.9	0.0977	0.0977	III	A3
0.1	-0.0000002407	-0.0000000241	0.2048703397	0.9	0.0951	0.0951	IV	A4
0.2	-0.0000000017	-0.0000000003	0.1145053639	0.8	0.0924	0.0924	II	A1
0.2	0.0000000000	0.0000000000	0.1115565387	0.8	0.0898	0.0898	I	A2
0.2	-0.0000000005	-0.0000000001	0.1220115125	0.8	0.0871	0.0871	III	A3
0.2	-0.0000002407	-0.0000000481	0.2048703397	0.8	0.0845	0.0845	IV	A4
0.3	-0.0000000017	-0.0000000005	0.1145053639	0.7	0.0818	0.0818	II	A1
0.3	0.0000000000	0.0000000000	0.1115565387	0.7	0.0792	0.0792	I	A2
0.3	-0.0000000005	-0.0000000002	0.1220115125	0.7	0.0765	0.0765	III	A3
0.3	-0.0000002407	-0.0000000722	0.2048703397	0.7	0.0739	0.0739	IV	A4

wt	score value	weight*score value	accuracy value	(1-wt)	(1-wt)* accuracy value	VIKOR index	Ranking	Alternatives
0.4	-0.0000000017	-0.0000000007	0.1145053639	0.6	0.0712	0.0712	II	A1
0.4	0.0000000000	0.0000000000	0.1115565387	0.6	0.0686	0.0686	I	A2
0.4	-0.0000000005	-0.0000000002	0.1220115125	0.6	0.0659	0.0659	III	A3
0.4	-0.0000002407	-0.0000000963	0.2048703397	0.6	0.0632	0.0632	IV	A4
0.5	-0.0000000017	-0.0000000009	0.1145053639	0.5	0.0606	0.0606	II	A1
0.5	0.0000000000	0.0000000000	0.1115565387	0.5	0.0579	0.0579	I	A2
0.5	-0.0000000005	-0.0000000003	0.1220115125	0.5	0.0553	0.0553	III	A3
0.5	-0.0000002407	-0.0000001204	0.2048703397	0.5	0.0526	0.0526	IV	A4
0.6	-0.0000000017	-0.0000000010	0.1145053639	0.4	0.0500	0.0500	II	A1
0.6	0.0000000000	0.0000000000	0.1115565387	0.4	0.0473	0.0473	I	A2
0.6	-0.0000000005	-0.0000000003	0.1220115125	0.4	0.0447	0.0447	III	A3
0.6	-0.0000002407	-0.0000001444	0.2048703397	0.4	0.0420	0.0420	IV	A4
0.7	-0.0000000017	-0.0000000012	0.1145053639	0.3	0.0394	0.0394	II	A1
0.7	0.0000000000	0.0000000000	0.1115565387	0.3	0.0367	0.0367	I	A2
0.7	-0.0000000005	-0.0000000004	0.1220115125	0.3	0.0341	0.0341	III	A3
0.7	-0.0000002407	-0.0000001685	0.2048703397	0.3	0.0314	0.0314	IV	A4
0.8	-0.0000000017	-0.0000000014	0.1145053639	0.2	0.0287	0.0287	II	A1
0.8	0.0000000000	0.0000000000	0.1115565387	0.2	0.0261	0.0261	I	A2
0.8	-0.0000000005	-0.0000000004	0.1220115125	0.2	0.0234	0.0234	III	A3
0.8	-0.0000002407	-0.0000001926	0.2048703397	0.2	0.0208	0.0208	IV	A4
0.9	-0.0000000017	-0.0000000015	0.1145053639	0.1	0.0181	0.0181	II	A1
0.9	0.0000000000	0.0000000000	0.1115565387	0.1	0.0155	0.0155	I	A2
0.9	-0.0000000005	-0.0000000005	0.1220115125	0.1	0.0128	0.0128	III	A3
0.9	-0.0000002407	-0.0000002166	0.2048703397	0.1	0.0102	0.0102	IV	A4
1.0	-0.0000000017	-0.0000000017	0.1145053639	0.0	0.0075	0.0075	II	A1
1.0	0.0000000000	0.0000000000	0.1115565387	0.0	0.0049	0.0049	I	A2
1.0	-0.0000000005	-0.0000000005	0.1220115125	0.0	0.0022	0.0022	III	A3

wt	score value	weight*score value	accuracy value	(1-wt)	(1-wt)* accuracy value	VIKOR index	Ranking	Alternatives
1.0	-0.0000002407	-0.0000002407	0.2048703397	0.0	-0.0004	-0.0004	IV	A4

8. Conclusion

In conclusion, our comparison of the TrIF VIKOR MCDM method with the score and accuracy function revealed interesting insights. The correlation analysis conducted between the VIKOR ranking, score function, and accuracy function ranking shed light on the relationship between these components. The positive correlation observed between the VIKOR ranking and accuracy function indicates that alternatives that were closer to the ideal solution, as measured by the accuracy function, tended to have higher rankings in the VIKOR method. This finding suggests that the accuracy function successfully captured the proximity of alternatives to the ideal solution, and the VIKOR method effectively incorporated this information in determining the compromise solution. This indicates that the VIKOR method considered other factors, such as the trade-offs and compromises among criteria, rather than relying solely on individual scores. By integrating both the score and accuracy function, the TrIF VIKOR MCDM technique facilitated a comprehensive assessment of the alternatives in the evaluation of metaverse platforms. The score function assigned scores based on the performance of each alternative for each criterion, while the accuracy function measured the proximity of alternatives to the ideal solution. The TrIF VIKOR MCDM technique effectively combined these functions to identify the compromise choice of a metaverse platform, considering both the individual criterion performance and the proximity to the ideal solution. This approach accounts for the complexities and trade-offs inherent in MCDM, providing DMs with a robust methodology for making informed choices. Additionally, the sensitivity analysis played a pivotal role in determining the optimal choice, highlighting alternative A2 (platform B) as the preferred option.

Overall, the correlation analysis and application of the TrIF VIKOR MCDM technique highlighted the interplay between the VIKOR ranking, score function, and accuracy function, showcasing their roles and contributions in the comprehensive assessment of alternatives in the context of evaluating metaverse platforms.

Author Contributions

Conceptualization, R.I. and V.A; methodology, R.I.; validation, R.I. and V.A; formal analysis, R.I.; investigation, R.I.; resources, R.I.; A.F. and V.A.; writing—original draft preparation, R.I.; writing—review and editing, R.I.; visualization, R.I.; supervision, A.F. and V.A.; The authors have read and agreed to the published version of the manuscript.

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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.

Data Availability Statement

The data used to support the findings of this study are included within the article.

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