University of New Mexico

An efficient Model for Satisfaction Evaluation of College Students' Online Ideological and Political Education with Single-Valued Neutrosophic Numbers

Kelei Shi
Shandong Women's University, Jinan, 250300, Shandong, China
Corresponding author: E-mail: 24004@sdwu.edu.cn

Abstract: Under the background of big data, the evaluation of college students' satisfaction with online ideological and political education (IAPE) is primarily achieved through data mining and analysis techniques, allowing for a more comprehensive and accurate reflection of students' attitudes and feedback. By collecting data through online surveys, social media interactions, and other channels, educators can adjust the content and methods of teaching in real-time to better meet students' needs and improve the effectiveness and satisfaction of IAPE. The satisfaction evaluation of college students' online IAPE in the context of big data is a multi-attribute group decision-making (MAGDM) problem. Recently, VIKOR method have been applied to address MAGDM challenges. Single-valued neutrosophic sets (SVNSs) are employed as a tool to represent uncertain data in the satisfaction evaluation of college students' online IAPE within the big data context. In this paper, we propose the single-valued neutrosophic number VIKOR (SVNN-VIKOR) method to solve MAGDM problems under SVNSs. Finally, a numerical case study is presented to validate the effectiveness of the proposed method in evaluating the satisfaction of college students' online IAPE in the context of big data.

Keywords: MAGDM; SVNSs; information entropy; VIKOR approach; satisfaction of college students' online IAPE

---

1. Introduction

In the context of big data, research on the satisfaction evaluation of college students' online ideological and political education has become an important topic in the field of education. With the rapid development of internet technology, online ideological and political education has become a crucial part of ideological and political education in universities. Through online platforms, students can access learning resources anytime and anywhere, participate in interactions, and enhance their political literacy. However, scientifically and comprehensively evaluating students' satisfaction with online ideological and political education is key to improving the quality and effectiveness of education. First, the evaluation of satisfaction requires the establishment of a multidimensional evaluation index system. Common indicators include platform usability and ease of operation, richness and practicality of content, interactivity (such as communication between students and teachers, or among students), the timeliness and quality of educational resources, and the effectiveness of students' learning and ideological progress. Additionally, emotional experiences, such as students' interest in the course, level of participation, and recognition of the ideological content, are also critical dimensions. Second, big data technologies can be used to achieve comprehensive satisfaction analysis. By collecting data on students' learning behaviors on the platform, such as study duration, interaction frequency, and assignment submissions, combined with surveys and online feedback, a thorough evaluation that combines both quantitative and qualitative analysis can be conducted. Finally, the research results should provide guidance for improving online ideological and political education, helping educators optimize teaching content and methods to enhance the effectiveness of political education for students. The satisfaction evaluation of college students' online IAPE in the context of big data represents a classical MAGDM problem. Decision-makers (DMs) often utilize SVNSs [1] in the satisfaction evaluation of college students' online IAPE in the context of big data. The SVNSs [1] offer significant advantages in handling uncertainty and fuzzy information. First, SVNSs can simultaneously represent truth, falsity, and indeterminacy, providing a more flexible modeling approach compared to traditional fuzzy sets or intuitionistic fuzzy sets. This allows for a precise description of uncertainty in complex systems. Second, SVNSs effectively address common issues of uncertainty and incomplete information in decision-making, especially in cases where information is ambiguous or contradictory. Third, SVNSs offer greater flexibility by independently representing truth, falsity, and indeterminacy in a three-dimensional space, thereby improving the accuracy and rationality of decisions. Finally, SVNSs are widely applied in areas such as multi-criteria decision-making, risk assessment, and medical diagnosis, making them particularly suitable for dealing with fuzzy and uncertain information in complex decision environments. Thus, SVNSs provide a powerful and flexible solution for uncertainty-related problems. However, due to limited knowledge about the decision domain and time constraints, the attribute weights are frequently unknown. This challenge motivated us to develop a novel decision-making approach to determine weight values based on entropy under SVNSs. Gomes and Lima [2] and Gomes and Lima [3] initially introduced the TODIM method for MADM under risk, and later, Leoneti and Gomes [4] proposed the Exponential TODIM (ExpTODIM). While many decision algorithms use ExpTODIM[4-6] and VIKOR[7, 8] methods independently to identify optimal decisions, few have explored the VIKOR under SVNSs. To address this gap, we propose an integrated SVNN-VIKOR method to solve the MAGDM problem. An illustrative example of satisfaction evaluation of college students' online IAPE in the context of big data, accompanied by a comparative analysis, is provided to validate the effectiveness and reliability of the SVNN-VIKOR approach.

The main contributions of this paper are:

(1) To design an information entropy method using SVNSs to derive weight information.

(2) To establish an integrated SVNN -VIKOR method to solve the MAGDM problem; and

(3) To present an illustrative example of satisfaction evaluation of college students' online IAPE in the context of big data to demonstrate the effectiveness of SVNN- -VIKOR method.

The structure of this paper is outlined: Section 2 introduces the literature review. Section 3 introduces the concept of SVNSs. In Section 4, the SVNN-VIKOR method, incorporating entropy, is developed under the SVNS framework. Section 5 presents an illustrative case study on the satisfaction evaluation of college students' online IAPE in the context of big data, along with a comparative analysis. Finally, concluding remarks are provided in Section 6.

2. Literature review

With the rapid development of internet technology, big data is injecting new vitality into IAPE in universities, driving powerful transformations in the field of higher education. The internet has become an essential domain for today's college students, which means that universities need to leverage big data technology to innovate and advance IPE work. This approach not only focuses on students' genuine needs but also seeks to gain their recognition, thus effectively fulfilling President Xi Jinping's directive for universities to make IPE "contextualized, timely, and innovative" [9]. Universities primarily utilize platforms such as official websites, WeChat public accounts, and TikTok to deliver IPE content. The satisfaction of college students with online IPE refers to their evaluation of the effectiveness of these virtual educational activities [10]. Although the concept of "IAPE" does not exist in foreign countries, extensive research has been conducted in areas such as civic education, moral education, and legal education. In the United States, advanced network technologies have facilitated the emergence of online education as a new form of IPE [11]. Compared to foreign studies on online IPE, Chinese scholars have conducted more detailed research on the subject, exploring it from various perspectives. From the standpoint of online platforms, online IPE in China primarily uses live streaming platforms, the "Xuexi Qiangguo" app, and short videos on TikTok to achieve high interactivity and real-time engagement. By employing big data technology, universities have enhanced their ability to educate and guide students in ideological and political matters, thereby improving the overall effectiveness of IPE [12, 13]. From the perspective of the educational environment, universities are utilizing artificial intelligence, big data, and other digital technologies to comprehensively monitor internet public opinion related to their institutions, placing online public opinion management as a high priority in campus governance. This approach ensures that students are guided toward the correct values, enhances their critical thinking skills, and fully realizes the educational function of IPE [14]. At the same time, universities are utilizing online IPE platforms to organize various online cultural activities, encouraging student participation and interaction, thereby increasing students' engagement and sense of belonging [15].

MAGDM is a decision-making method where multiple decision-makers evaluate and select from multiple alternatives based on several attributes or criteria [16-18]. This method is widely used in complex decision-making scenarios, especially when multiple stakeholders are involved, and a variety of factors need to be considered, such as project evaluation, policy making, and supplier selection [19]. The core of MAGDM lies in balancing the weights of different attributes and forming a rational decision outcome from the information provided by different DMs [20, 21]. In practice, there are two main challenges: first, how to handle the trade-offs between different attributes, and second, how to integrate the preferences and opinions of multiple DMs [22, 23]. To address these issues, common methods include weighted averaging, Analytic Hierarchy Process (AHP), fuzzy set theory, and entropy weighting methods. These approaches aim to assign appropriate weights to each attribute to comprehensively evaluate the advantages and disadvantages of each option. In situations with high uncertainty (such as incomplete or fuzzy information), methods like SVNS and grey system theory are widely used to better handle uncertain data. In recent years, hybrid decision-making models that combine various methods, such as VIKOR [7, 8], have become a research focus in MAGDM. These methods integrate different decision tools to provide more flexible and accurate decision support. The ultimate goal of MAGDM is to synthesize various pieces of information and the opinions of decision-makers to arrive at an optimal or near-optimal decision, ensuring fairness and rationality in the decision-making process[24, 25].

2. Preliminaries

Wang et al. [1] designed the SVNSs

Definition 1 [1]. The SVNSs is designed:

$$YA=\left\{\left(\phi,YT_A\left(\phi\right),YI_A\left(\phi\right),YF_A\left(\phi\right)\right)\middle|\phi\in\Phi\right\} \quad (1)$$

where $YT_A\left(\phi\right),YI_A\left(\phi\right),YF_A\left(\phi\right)$ designed the truth-membership, indeterminacy-membership and falsity-membership, $YT_A\left(\phi\right),YI_A\left(\phi\right),YF_A\left(\phi\right)\in\left[0,1\right]$ and satisfies $0\le YT_A\left(\phi\right)+YI_A\left(\phi\right)+YF_A\left(\phi\right)\le 3$.

The single-valued neutrosophic number (SVNN) is designed as $YA=\left(YT_A,YI_A,YF_A\right)$, where $YT_A,YI_A,YF_A\in\left[0,1\right]$, and $0\le YT_A+YI_A+YF_A\le 3$.

Definition 2 [26]. Let $YA=\left(YT_A,YI_A,YF_A\right)$ and $YB=\left(YT_B,YI_B,YF_B\right)$ be SVNN, score values are designed:

$$SV\left(YA\right)=\frac{\left(2+YT_A-YI_A-YF_A\right)}{3},\ S\left(YA\right)\in\left[0,1\right]. \quad (2\text{-a})$$

$$SV(YB)=\frac{(2+YT_B-YI_B-YF_B)}{3},\ S(YB)\in[0,1]. \quad (2\text{-a})$$

Definition 3[26]. Let $YA=(YT_A,YI_A,YF_A)$ and $YB=(YT_B,YI_B,YF_B)$ be SVNN, an accuracy value is designed:

$$HV(YA)=YT_A-YF_A,\ AV(YA)\in[-1,1]. \quad (3)$$

$$HV(YB)=YT_B-YF_B,\ AV(YB)\in[-1,1]. \quad (3)$$

Peng, Wang, Wang, Zhang and Chen [26] designed the order for SVNNs.

Definition 4[26]. Let $YA=(YT_A,YI_A,YF_A)$ and $YB=(YT_B,YI_B,YF_B)$ be two given SVNNs, $SV(YA)=\frac{(2+YT_A-YI_A-YF_A)}{3}$ and $SV(YB)=\frac{(2+YT_B-YI_B-YF_B)}{3}$, and $HV(YA)=YT_A-YF_A$ and $HV(YB)=YT_B-YF_B$, then if $SV(YA)<SV(YB)$, then $YA<YB$; if $SV(YA)=SV(YB)$, then (1)if $AV(YA)=AV(YB)$, then $YA=YB$; (2) if $AV(YA)<AV(YB)$, then $YA<YB$.

Definition 5[1]. Let $YA=(YT_A,YI_A,YF_A)$ and $YB=(YT_B,YI_B,YF_B)$ be SVNNs, basic operations are designed:

(1) $YA\oplus YB=(YT_A+YT_B-YT_AYT_B,YI_AYI_B,YF_AYF_B)$;
(2) $YA\otimes YB=(YT_AYT_B,YI_A+YI_B-YI_AYI_B,YF_A+YF_B-YF_AYF_B)$;
(3) $\lambda YA=\left(1-(1-YYT_A)^{\lambda},(YI_A)^{\lambda},(YF_A)^{\lambda}\right),\lambda>0;$
(4) $(YA)^{\lambda}=\left((YT_A)^{\lambda},(YI_A)^{\lambda},1-(1-YF_A)^{\lambda}\right),\lambda>0.$

Definition 6[27]. Let $YA=(YT_A,YI_A,YF_A)$ and $YB=(YT_B,YI_B,YF_B)$, the SVNN Hamming distance (SVNNHD) is designed:

$$SVNNHD(XA,XB)=\frac{|YT_A-YT_B|+|YI_A-YI_B|+|YF_A-YF_B|}{3} \quad (4)$$

The SVNNWA and SVNNWG approach is designed:

Definition 7[26]. Let $YA_j=(YT_j,YI_j,YF_j)$ be SVNNs, the SVNNWA is designed:

$$
\begin{aligned}
&\mathrm{SVNNWA}\left(YA_1, YA_2, \ldots, YA_n\right) \\
&= yw_1 YA_1 \oplus yw_2 YA_2 \ldots \oplus yw_n YA_n = \overset{n}{\underset{j=1}{\oplus}} yw_j YA_j \\
&= \left(1-\prod_{j=1}^{n}\left(1-YT_{ij}\right)^{yw_j}, \prod_{k=1}^{l}\left(YF_{ij}\right)^{yw_j}, \prod_{k=1}^{l}\left(YT_{ij}\right)^{yw_j}\right)
\end{aligned} \tag{5}
$$

where $yw = \left(yw_1, yw_2, \ldots, yw_n\right)^T$ be weight of YA_j , $yw_j > 0, \sum_{j=1}^{n} yw_j = 1.$

Definition 8[26]. Let $YA_j = \left(YT_j, YI_j, YF_j\right)$ be SVNNs, the SVNNWG approach is designed:

$$
\begin{aligned}
&\mathrm{SVNNWG}\left(YA_1, YA_2, \ldots, YA_n\right) \\
&= \left(YA_1\right)^{yw_1} \otimes \left(YA_2\right)^{yw_2}, \ldots \otimes \left(YA_n\right)^{yw_n} = \overset{n}{\underset{j=1}{\otimes}} \left(YA_j\right)^{yw_j} \\
&= \left(\prod_{j=1}^{n}\left(YT_{ij}\right)^{yw_j}, 1-\prod_{j=1}^{n}\left(1-YF_{ij}\right)^{yw_j}, 1-\prod_{j=1}^{n}\left(1-YT_{ij}\right)^{yw_j}\right)
\end{aligned} \tag{6}
$$

where $yw = \left(yw_1, yw_2, \ldots, yw_n\right)^T$ be weight of YA_j , $yw_j > 0, \sum_{j=1}^{n} yw_j = 1.$

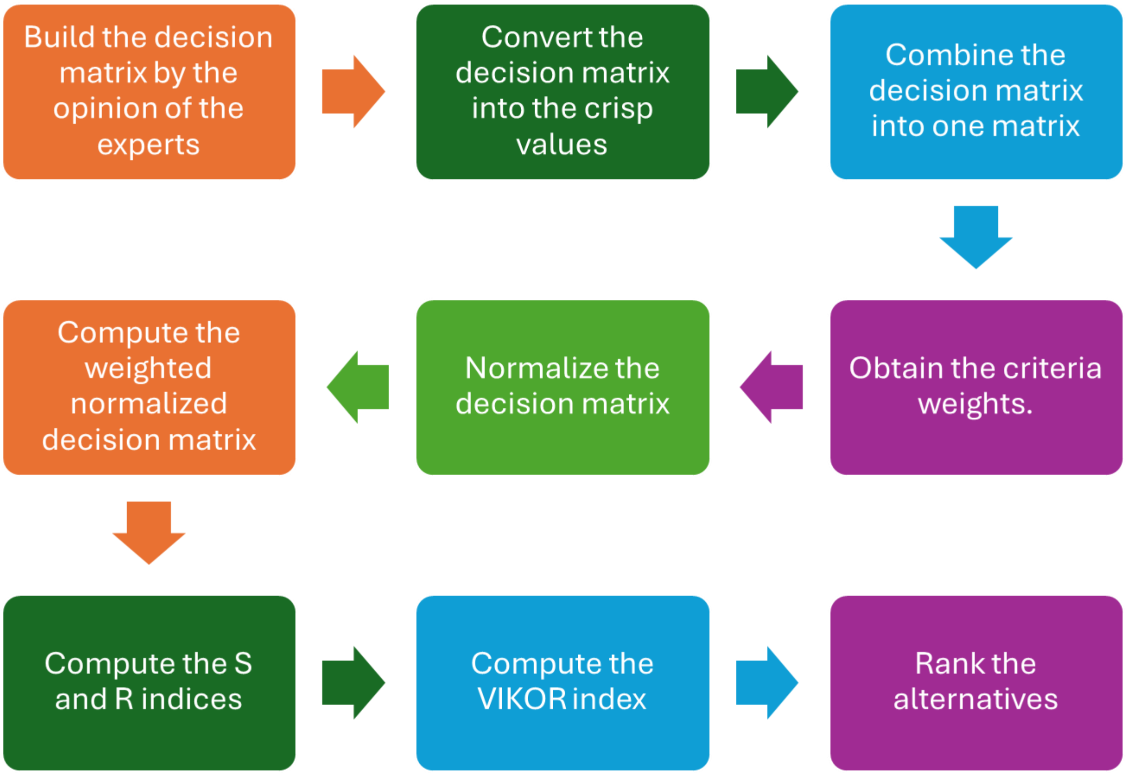

Figure 1. The steps of the SVNN-VIKOR.

3. Materials and Methods

3.1 SVNN-VIKOR Method

VIKOR method is a MAGDM method used to rank the alternatives. The criteria in this method are independent and the qualitative criteria are changed into quantitative criteria. The steps of the SVNN-VIKOR method are shown in Figure 1.

1. Build the decision matrix by the opinion of the experts

$$X^D = \begin{bmatrix} y_{11}^D & \cdots & y_{1n}^D \\ \vdots & \ddots & \vdots \\ y_{m1}^D & \cdots & y_{mn}^D \end{bmatrix} \quad (7)$$

Where $i = 1,2, \ldots, n; j = 1,2, \ldots m$.

2. Convert the decision matrix into the crisp values.

3. Combine the decision matrix into one matrix.

$$X = \begin{bmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{bmatrix} \quad (8)$$

4. Obtain the criteria weights.

The criteria weights are obtained using the average method.

5. Normalize the decision matrix

$$N_{ij} = \frac{\max y_{ij} - y_{ij}}{\max y_{ij} - \min y_{ij}} \quad (9)$$

6. Compute the weighted normalized decision matrix

$$U_{ij} = w_j * N_{ij} \quad (10)$$

7. Compute the S and R indices

$$S_i = \sum_{j=1}^{n} U_{ij} \quad (11)$$

$$R_i = \max U_{ij}$$

8. Compute the VIKOR index

$$G_i = L * \left(\frac{S_i - \min S_i}{\max S_i - \min S_i}\right) + (1 - L) * \left(\frac{R_i - \min R_i}{\max R_i - \min R_i}\right) \quad (12)$$

Where L refers to the strategic weight and value equal to 0.5.

4. Numerical example and comparative analysis

4.1. Numerical Example for satisfaction evaluation of college students' online IAPE

In the context of big data, the satisfaction evaluation of college students' online IAPE has undergone significant changes. Traditional satisfaction evaluations often relied on surveys or a limited number of interviews, which provided only a small amount of data and made it difficult to comprehensively reflect students' true feelings. The introduction of big data technology allows educators to obtain information about students' learning behavior, interactions, and feedback from multiple channels and dimensions, enabling more accurate and dynamic satisfaction evaluations. Firstly, big data can collect and process data from various sources in real time, such as usage records from online course platforms, social media comments, and learning interactions. This data includes not only explicit feedback from students (such as ratings and comments) but also implicit behaviors (such as time spent on learning, click rates on pages, frequency of participation in discussions, etc.), providing a more comprehensive perspective for satisfaction evaluation. Secondly, big data analysis helps educators identify different needs and preferences among student groups. By performing statistical and clustering analysis on large datasets, it is possible to discover how students from different backgrounds and with varying learning habits respond differently to online IAPE, thus offering a basis for personalized teaching. This precise analysis can effectively enhance the relevance of education and students' sense of engagement, thereby improving overall satisfaction. Furthermore, big data technology allows educators to dynamically adjust teaching content and methods based on real-time feedback. In the past, evaluations often lagged behind actual teaching, but now, through real-time analysis of big data, educators can quickly understand students' attitudes and learning outcomes, and make timely adjustments to course settings and teaching strategies, thus improving the quality of education. In conclusion, with the support of big data technology, the satisfaction evaluation of college students' online IAPE is not only more comprehensive and accurate but also has the ability to make dynamic adjustments, providing strong support for the optimization and improvement of IAPE. The satisfaction evaluation of college students’ online IAPE in the context of big data is MAGDM.

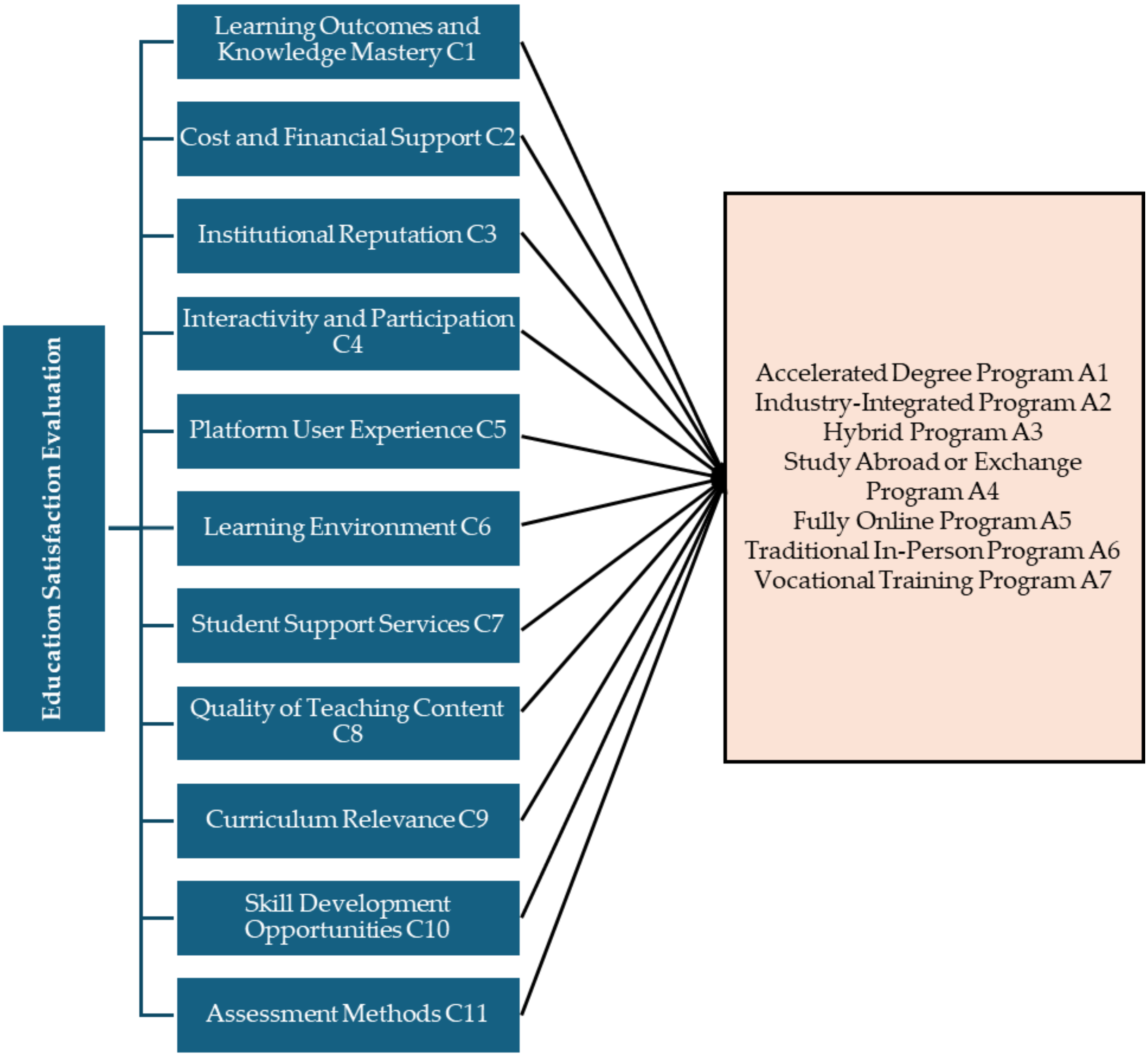

Figure 2. The criteria and alternatives.

We applied the SVNN-VIKOR with 11 criteria and 7 alternatives as shown in Figure 2.

1. Four experts evaluated the criteria and alternatives. They used SVNN. Tables A1-A4.
2. We converted SVNN into crisp values.
3. We combined the decision matrix into one matrix as shown in Table 1.

Table 1. The combined decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.470833	0.620833	0.404167	0.225	0.691667	0.7125	0.7125
C_2	0.341667	0.641667	0.445833	0.508333	0.404167	0.270833	0.616667
C_3	0.445833	0.608333	0.620833	0.379167	0.579167	0.204167	0.5
C_4	0.570833	0.804167	0.466667	0.404167	0.65	0.754167	0.333333
C_5	0.591667	0.65	0.620833	0.445833	0.629167	0.804167	0.166667
C_6	0.720833	0.470833	0.529167	0.445833	0.629167	0.783333	0.066667
C_7	0.783333	0.320833	0.775	0.5875	0.4875	0.5875	0.066667

C_8	0.670833	0.508333	0.670833	0.629167	0.558333	0.570833	0.866667
C_9	0.691667	0.641667	0.4	0.375	0.3625	0.516667	0.783333
C_{10}	0.245833	0.629167	0.6	0.5375	0.491667	0.166667	0.783333
C_{11}	0.291667	0.558333	0.5375	0.4875	0.416667	0.616667	0.616667

4. Then we will compute the criteria weights as shown in Figure 3. we show the criterion 8 has the highest weight and criterion 2 has the lowest weight.

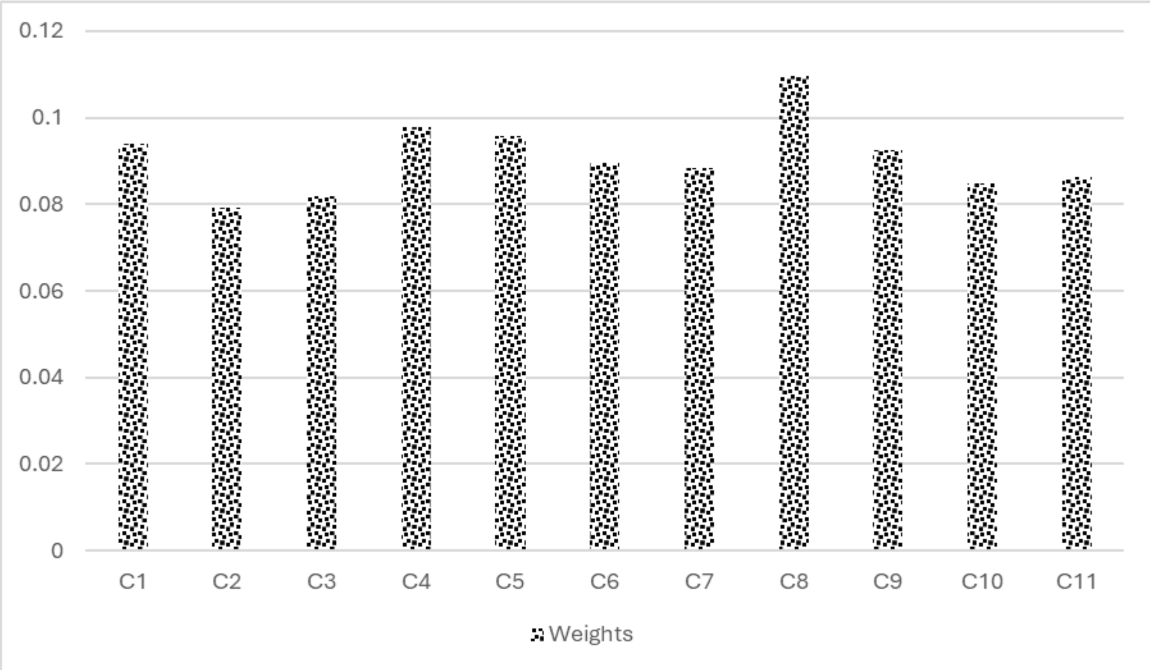

Figure 3. The criteria weights.

5. We normalized the decision matrix as shown in Table 2.

Table 2. The normalized decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.495726	0.188034	0.632479	1	0.042735	0	1.03E-09
C_2	0.191011	1	0.47191	0.640449	0.359551	0	0.932584
C_3	0.42	0.03	0	0.58	0.1	1	0.29
C_4	0.495575	0	0.716814	0.849558	0.327434	0.106195	1
C_5	0.333333	0.24183	0.287582	0.562092	0.27451	0	1
C_6	0.087209	0.436047	0.354651	0.47093	0.215116	0	1
C_7	0	0.645349	0.011628	0.273256	0.412791	0.273256	1
C_8	0.546512	1	0.546512	0.662791	0.860465	0.825581	0
C_9	0.217822	0.336634	0.910891	0.970297	1	0.633663	0
C_{10}	0.871622	0.25	0.297297	0.398649	0.472973	1	0
C_{11}	1.625	0.291667	0.395833	0.645833	1	0	0

6. We compute the weighted normalized decision matrix as shown in Table 3.

Table 3. The weighted normalized decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	0.046655	0.017697	0.059525	0.094114	0.004022	0	9.65E-11
C_2	0.015127	0.079195	0.037373	0.05072	0.028475	0	0.073856
C_3	0.034378	0.002456	0	0.047474	0.008185	0.081852	0.023737

C_4	0.048413	0	0.070026	0.082994	0.031987	0.010374	0.097691
C_5	0.03195	0.02318	0.027565	0.053877	0.026312	0	0.095851
C_6	0.007798	0.038988	0.031711	0.042107	0.019234	0	0.089413
C_7	0	0.057109	0.001029	0.024181	0.036529	0.024181	0.088494
C_8	0.059979	0.109749	0.059979	0.07274	0.094435	0.090606	0
C_9	0.020144	0.031132	0.084238	0.089732	0.092479	0.058601	0
C_{10}	0.073838	0.021178	0.025185	0.033771	0.040067	0.084713	0
C_{11}	0.140481	0.025215	0.03422	0.055832	0.08645	0	0

7. We compute the S and R indices.
8. We complete the VIKOR index we put the L with 0.5 as shown in Figure 4. We show the alternative 6 is the best and alternative 1 is the worst.

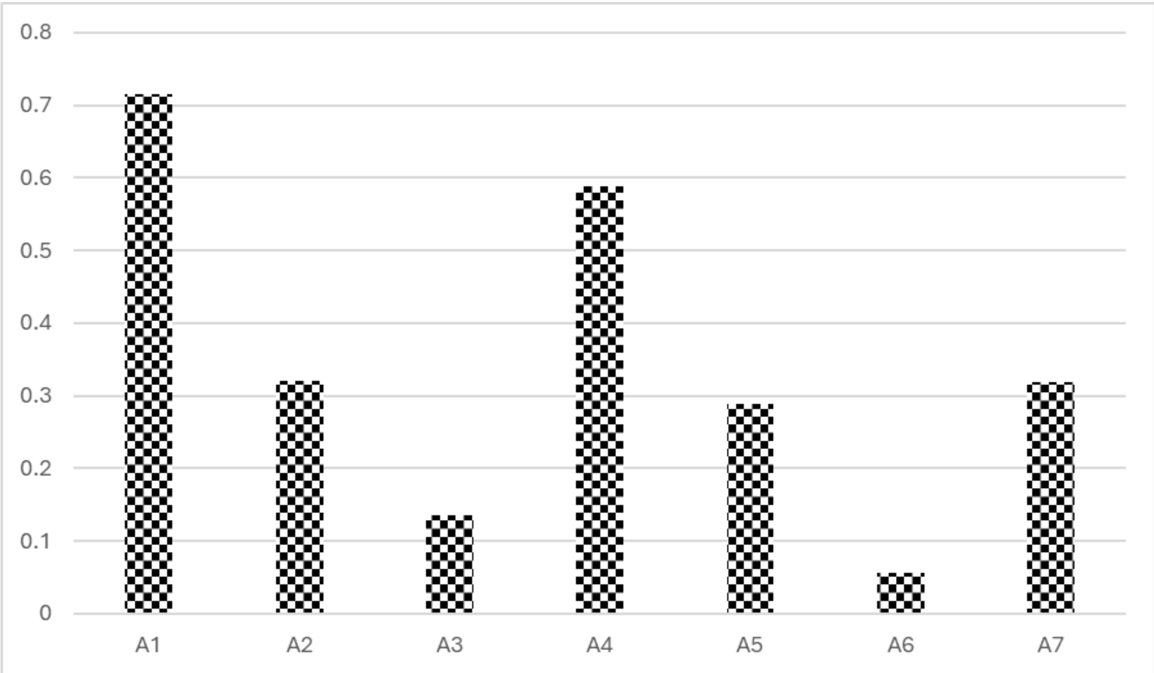

Figure 4. The values of VIKOR index.

4.2. Sensitivity analysis and discussion analysis

We adjust the L parameter in the VIKOR index. We put the values between 0 to 1 and show the rank of alternatives. We show alternative 6 is the best as shown in Figure 5. So, we show the rank of alternatives is stable.

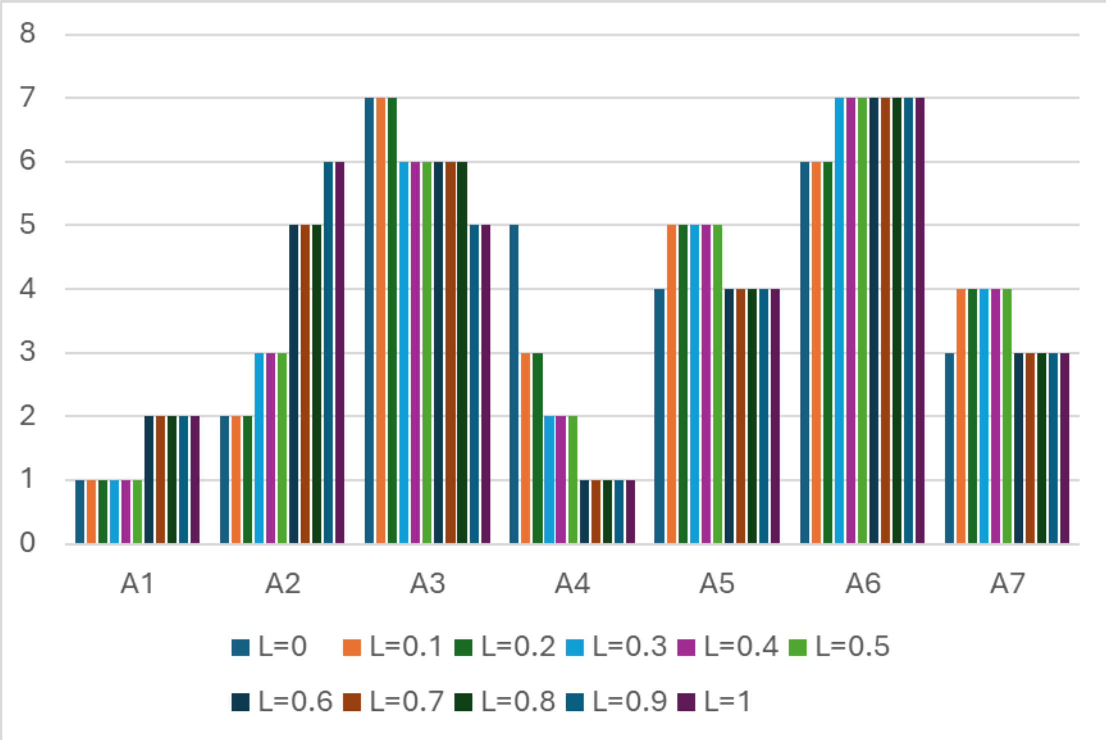

Figure 5. The rank of alternatives under different L parameters.

In contrast, the SVNN-VIKOR approach proposed in this paper offers the following three main advantages: **(1) High Flexibility**: This method effectively addresses MAGDM problems with uncertainty and fuzziness, particularly within the framework of SVNSs, providing a more accurate representation of uncertain information in decision-making. **(2) Improved Computational Efficiency**: Compared to some existing methods, SVNN-VIKOR exhibits relatively lower computational complexity when handling multiple decision-makers and attributes, maintaining high accuracy while reducing the computational burden. **(3) Good Consistency in Decision Results**: In comparison with other methods, SVNN-VIKOR demonstrates superior performance in terms of ranking consistency and rationality of results, confirming its effectiveness and reasonableness in solving MAGDM problems.

However, despite these advantages, the proposed method also has the following two limitations: (1) **High Sensitivity to Parameters**: Certain parameters in the SVNN-VIKOR method significantly impact the results, which may lead to instability in different decision-making scenarios, requiring parameter tuning to ensure optimal performance. (2) **Increased Complexity in Application**: Compared to some more straightforward methods, the theoretical framework and computational process of this approach are relatively complex, which may demand higher levels of expertise and computational capacity from users, thus increasing the difficulty of practical application.

Overall, while the proposed method demonstrates notable advantages in flexibility, efficiency, and result consistency, there is still room for improvement in terms of parameter sensitivity and application complexity.

5. Conclusion and future research directions

In the context of big data, the satisfaction evaluation of college students' online IAPE is primarily achieved through advanced data collection and analysis techniques. By utilizing various channels such as online surveys, social media interactions, and learning platform data, comprehensive feedback and behavioral data from students can be gathered. Big data technology not only provides real-time feedback but also uncovers students' focal points, interests, and learning challenges through in-depth analysis. This data offers educators scientific insights, enabling them to optimize content and methods to better meet students' individual needs. Additionally, machine learning and AI technologies assist in analyzing students' satisfaction with online IAPE, predicting educational outcomes, and offering targeted improvement suggestions. Ultimately, big data-based satisfaction evaluation effectively enhances the quality of online IAPE and improves students' learning experiences. The satisfaction evaluation of college students' online IAPE in the context of big data is MAGDM. Recently, the VIKOR method has been utilized to address MAGDM problems, with SVNSs employed to represent uncertain information in satisfaction evaluations. In this paper, we introduce the SVNN-VIKOR model to solve MAGDM within the framework of SVNSs. Lastly, a numerical case study focused on the satisfaction evaluation of college students' online IAPE in the context of big data is presented to validate the effectiveness of the proposed method.

Although the SVNN-VIKOR method proposed in this paper demonstrates significant advantages in evaluating the satisfaction of college students' online IAPE in the context of big data, there are several research limitations that merit attention. First, **the complexity of the model is relatively high**. While the SVNN-VIKOR method effectively handles uncertain information, its computational process is complex. This complexity, especially when dealing with large datasets, results in high computational time and resource consumption, potentially making it less suitable for real-time decision-making scenarios. Second, **parameter tuning issues**. The SVNN-VIKOR model is highly sensitive to the selection of certain parameters, which significantly affect the final outcome. The sensitivity to these parameters means that different parameter choices can lead to varying decision results, thereby impacting the model's stability and generalizability. Lastly, **a lack of extensive empirical validation**. Although the effectiveness of the method is verified through a numerical case study, it is limited to a specific scenario with simulated data. The model's applicability and robustness in other fields or real-world applications have not yet been fully tested, lacking broad empirical case support.

Based on the above research limitations, future studies can explore the following three directions:(1)**Optimizing the computational efficiency of the model:** To improve the applicability of the SVNN-VIKOR method for large datasets, further research can focus on incorporating parallel computing, distributed computing, and other techniques to optimize the algorithm's computational efficiency. This would reduce time and resource consumption, making the method more suitable for real-time decision-making, particularly in dynamic data environments. (2) **Parameter optimization and automatic tuning mechanisms:** To address the limitation of parameter sensitivity, future research could explore the use of intelligent optimization algorithms (such as genetic algorithms, particle swarm optimization, etc.) to automatically tune the parameters. This would reduce the subjectivity in parameter settings and improve the model's adaptability and stability across different scenarios. (3) **Empirical studies and application expansion across multiple fields:** Beyond the satisfaction evaluation of online IAPE, future research could apply the SVNN-VIKOR method in other educational or non-educational fields for broader empirical validation. By testing and verifying the method in various domains, the generalizability of the approach can be further evaluated, enhancing its application value across multiple fields and scenarios.

References

[1] H. Wang, F. Smarandache, Y.Q. Zhang, R. Sunderraman, Single valued neutrosophic sets, Multispace Multistruct, (2010) 410-413.

[2] L. Gomes, M. Lima, Todim: Basics and apllication to multicriteria ranking of projects with environmental impacts, Foundations of Control Engineering, 16 (1991) 113-127.

[3] L.F.A.M. Gomes, M.M.P.P. Lima, From modeling individual preferences to multicriteria ranking of discrete alternatives: A look at prospect theory and the additive difference model, Foundations of

Computing and Decision Sciences, 17 (1992) 171-184.

[4] A.B. Leoneti, L. Gomes, A novel version of the todim method based on the exponential model of prospect theory: The exptodim method, European Journal of Operational Research, 295 (2021) 1042-1055.

[5] Y. Deng, W.X. Zhang, An exptodim-gra based multiple attribute group decision-making method for development level evaluation of digital inclusive finance under intuitionistic fuzzy circumstances, Journal of Intelligent & Fuzzy Systems, 45 (2023) 10661-10673.

[6] H. Sun, Z. Yang, Q. Cai, G. Wei, Z. Mo, An extended exp-todim method for multiple attribute decision making based on the z-wasserstein distance, Expert Systems with Applications, 214 (2023) 119114.

[7] S. Opricovic, G.H. Tzeng, Compromise solution by mcdm methods: A comparative analysis of vikor and topsis, European Journal of Operational Research, 156 (2004) 445-455.

[8] S. Opricovic, G.H. Tzeng, Extended vikor method in comparison with outranking methods, European Journal of Operational Research, 178 (2007) 514-529.

[9] J. Wu, H. Hu, Incorporating ideological and political work throughout the entire education process to create a new situation in the development of higher education in china, Shanghai Education, 2017 (2017) 4-5.

[10] Y. Fang, L. Huang, N. Lan, et al., Research on enhancing college students' sense of gain in online ideological and political education based on the yiban platform, Western Journal, 2021 (2021) 107-109.

[11] X. Yu, The "five educations" and "three natures" of ideological and political education in the united states, Contemporary World and Socialism, 2011 (2011) 166-171.

[12] H. Geng, Feasibility analysis of ideological and political education for "post-95" college students based on online live streaming platforms, Journal of Changzhou Vocational Institute of Information Technology, 2017 (2017) 83-86.

[13] H. Zhang, Research on the role of network media in promoting ideological and political education for young people: A case study of the xuexi qiangguo platform and tiktok short videos, Media Forum, 2020 (2020) 166-167.

[14] C. Hu, J. He, Optimizing ideological and political education in universities from the perspective of online public opinion, Journal of Liaoning Open University, 2023 (2023) 62-65.

[15] J. Ma, Research on college students' satisfaction with university online ideological and political micro-platforms and countermeasures, Taste · Classics, 2023 (2023) 90-93,106.

[16] A.A. El-Douh, S. Lu, A. Abdelhafeez, A.M. Ali, A.S. Aziz, Heart disease prediction under machine learning and association rules under neutrosophic environment, Neutrosophic Systems with Applications, 10 (2023) 35-52.

[17] K. M. Sallam, A.W. Mohamed, Single valued neutrosophic sets for assessment quality of suppliers under uncertainty environment, Multicriteria Algorithms with Applications, 1 (2023) 1-10.

[18] N. N.Mostafa, A. Krishan Kumar, Y. Ali, A comparative study on x-ray image enhancement based on neutrosophic set, Sustainable Machine Intelligence Journal, 7 (2024) (2):1-10.

[19] M. Abdel-Baset, V. Chang, A. Gamal, Evaluation of the green supply chain management practices: A novel neutrosophic approach, Computers in Industry, 108 (2019) 210-220.

[20] L. Niu, J. Ye, Magdm technique based on linguistic neutrosophic tangent dombi aggregation operators and its application in selecting new energy design schemes, Neutrosophic Sets and Systems, 70 (2024) 137-154.

[21] A. Kanchana, D. Nagarajan, S. Broumi, Multi-attribute group decision-making based on the neutrosophic bonferroni mean operator, Neutrosophic Sets and Systems, 57 (2023) 139-164.

[22] X.D. Peng, J.G. Dai, F. Smarandache, Research on the assessment of project-driven immersion teaching in extreme programming with neutrosophic linguistic information, International Journal of Machine Learning and Cybernetics, 14 (2023) 873-888.

[23] L.T.H. Lan, D.T. Hien, N.T. Thong, F. Smarandache, N.L. Giang, An anp-topsis model for tourist destination choice problems under temporal neutrosophic environment, Applied Soft Computing, 136 (2023) 12.

[24] Z. Wang, Q. Cai, G. Wei, Modified todim method based on cumulative prospect theory with type-2 neutrosophic number for green supplier selection, Engineering Applications of Artificial Intelligence, 126 (2023) 106843.

[25] B. Chen, Q. Cai, G. Wei, Z. Mo, Novel aczel-alsina operations-based linguistic z-number aggregation operators and their applications in multi-attribute group decision-making process, Engineering Applications of Artificial Intelligence, 124 (2023) 106541.

[26] J.J. Peng, J.Q. Wang, J. Wang, H.Y. Zhang, X.H. Chen, Simplified neutrosophic sets and their

applications in multi-criteria group decision-making problems, International Journal of Systems Science, 47 (2016) 2342-2358.

[27] P. Majumdar, S.K. Samanta, On similarity and entropy of neutrosophic sets, Journal of Intelligent & Fuzzy Systems, 26 (2014) 1245-1252.

Appendix

Table A1. The first decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.1,0.9,1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.1,0.9,1)	(0.9,0.2,0.1)	(0.9,0.2,0.1)	(0.85,0.3,0.2)
C_2	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.2,0.8,0.9)	(0.1,0.9,1)	(0.65,0.4,0.4)
C_3	(0.4,0.7,0.7)	(0.65,0.4,0.4)	(0.4,0.7,0.7)	(0.1,0.9,1)	(0.9,0.2,0.1)	(0.1,0.9,1)	(0.5,0.5,0.5)
C_4	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.2,0.8,0.9)	(0.9,0.2,0.1)	(0.9,0.2,0.1)	(0.4,0.7,0.7)
C_5	(0.5,0.5,0.5)	(0.9,0.2,0.1)	(0.65,0.4,0.4)	(0.4,0.7,0.7)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.2,0.8,0.9)
C_6	(0.65,0.4,0.4)	(0.1,0.9,1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.1,0.9,1)
C_7	(0.85,0.3,0.2)	(0.2,0.8,0.9)	(0.9,0.2,0.1)	(0.65,0.4,0.4)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.1,0.9,1)
C_8	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.9,0.2,0.1)
C_9	(0.9,0.2,0.1)	(0.5,0.5,0.5)	(0.1,0.9,1)	(0.2,0.8,0.9)	(0.4,0.7,0.7)	(0.4,0.7,0.7)	(0.85,0.3,0.2)
C_{10}	(0.1,0.9,1)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.1,0.9,1)	(0.2,0.8,0.9)	(0.85,0.3,0.2)
C_{11}	(0.1,0.9,1)	(0.2,0.8,0.9)	(0.2,0.8,0.9)	(0.4,0.7,0.7)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.65,0.4,0.4)

Table A2. The second decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)
C_2	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.65,0.4,0.4)
C_3	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.1,0.9,1)	(0.5,0.5,0.5)
C_4	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.4,0.7,0.7)
C_5	(0.5,0.5,0.5)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.2,0.8,0.9)
C_6	(0.65,0.4,0.4)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.85,0.3,0.2)	(0.1,0.9,1)
C_7	(0.85,0.3,0.2)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.65,0.4,0.4)	(0.1,0.9,1)
C_8	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.9,0.2,0.1)
C_9	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.85,0.3,0.2)
C_{10}	(0.1,0.9,1)	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.2,0.8,0.9)	(0.85,0.3,0.2)
C_{11}	(0.2,0.8,0.9)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.65,0.4,0.4)

Table A3. The third decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)
C_2	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.1,0.9,1)	(0.65,0.4,0.4)
C_3	(0.4,0.7,0.7)	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.1,0.9,1)	(0.5,0.5,0.5)

C_4	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.4,0.7,0.7)
C_5	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.2,0.8,0.9)
C_6	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.1,0.9,1)
C_7	(0.85,0.3,0.2)	(0.2,0.8,0.9)	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.1,0.9,1)
C_8	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.9,0.2,0.1)
C_9	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.4,0.7,0.7)	(0.4,0.7,0.7)	(0.85,0.3,0.2)
C_{10}	(0.1,0.9,1)	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.2,0.8,0.9)	(0.85,0.3,0.2)
C_{11}	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.5,0.5,0.5)	(0.65,0.4,0.4)	(0.65,0.4,0.4)

Table A4. The fourth decision matrix.

	A_1	A_2	A_3	A_4	A_5	A_6	A_7
C_1	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.9,0.2,0.1)	(0.85,0.3,0.2)
C_2	(0.2,0.8,0.9)	(0.85,0.3,0.2)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)
C_3	(0.85,0.3,0.2)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.5,0.5,0.5)
C_4	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.9,0.2,0.1)	(0.4,0.7,0.7)
C_5	(0.5,0.5,0.5)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.2,0.8,0.9)
C_6	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.85,0.3,0.2)	(0.1,0.9,1)
C_7	(0.85,0.3,0.2)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.1,0.9,1)
C_8	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.5,0.5,0.5)	(0.9,0.2,0.1)
C_9	(0.9,0.2,0.1)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.85,0.3,0.2)
C_{10}	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.2,0.8,0.9)	(0.85,0.3,0.2)
C_{11}	(0.1,0.9,1)	(0.85,0.3,0.2)	(0.9,0.2,0.1)	(0.4,0.7,0.7)	(0.2,0.8,0.9)	(0.65,0.4,0.4)	(0.65,0.4,0.4)

Received: July 26, 2024. Accepted: Oct 22, 2024