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# Assessing the Educational Effectiveness of Party-Building Activities in Universities under Neutrosophic Confidence Cubic Sets within Contemporary Higher Education Environments

Qi Jiang*

Suzhou Vocational University, Suzhou, 215100, Jiangsu, China

*Corresponding author, E-mail: abel198419@126.com

**Abstract**: Party-building exercises are essential to foster political literacy and social responsibility in students within the framework of ideological education and civic growth in higher education institutions. However, a methodical assessment based on pertinent criteria is necessary to guarantee their efficacy in teaching. This study offers a thorough methodology for evaluating the learning results of party-building activities at the university level. This study offers a clear roadmap for enhancing the planning and execution of these operations by comparing various implementation methods and identifying important performance metrics. A multi-criteria decision-making (MCDM) process is used to improve the evaluation's depth and dependability. The MOOSRA method is used to rank the alternatives. The Neutrosophic Confidence Cubic Sets is used to overcome uncertainty and vague information. The results are intended to provide educators and policymakers working on ideological and political education reform with useful advice.

**Keywords**: Neutrosophic Confidence Cubic Sets; Educational Effectiveness; Party-Building Activities; Universities.

## 1. Introduction

University party-building initiatives are a vital tool for fostering students' political participation, ideological knowledge, and shared ideals. These programs have an impact on future professionals' moral growth in addition to reaffirming the Communist Party's dominance over academic settings[1], [2]. Despite their strategic significance, these activities' educational value frequently lacks quantifiable assessment criteria, which results in uneven implementation throughout institutions. Conventional assessment methods place greater emphasis on participation rates than on behavioral effect or learning outcomes[3], [4]. The growing focus on responsibility and quality in education calls for a change to outcome-based evaluation techniques. In this sense, a methodical and open assessment system for party-building exercises can guarantee that they serve their educational objective more successfully. By proposing a methodology that considers several aspects of educational efficacy, this study aims to close this gap. It combines behavioral, emotional, and cognitive criteria to assess party-building activities' long-term effects in addition to student participation[5], [6].

Ideological understanding, value internalization, leadership development, civic duty, organizational involvement, and inventive engagement are the six main criteria that are suggested to direct the evaluation process. A fundamental component of successful political education is reflected in each of these[7].

Six options—representing different kinds of party-building models—are looked at to put these requirements into context. These options include peer mentorship, online ideological education, volunteer service programs, college cultural events, themed lectures, and collaborative efforts with neighborhood groups[8], [9].

This study evaluates the relative success of each option utilizing methodical process and decision-making tools. It is anticipated that the results will guide strategic planning and ongoing enhancements to political and ideological teaching at academic institutions.

Next, a broader platform was added to the cubic set, creating a Neutrosophic Cubic Set (NCS). Researchers suggested several NCS aggregation operators for decision-making. Q-neutrosophic cubic sets in two-dimensional universal sets and their weighted aggregation operators were proposed and used in MCDM issues using simultaneous interval and single-valued neutrosophic (SVN) information. Researchers introduced confidence levels in the fuzzy multi-valued setting and presented an exponential similarity measure of Confidence Neutrosophic Number Cubic Sets (CNNCSs) and used it to MCDM issues[10], [11].

To better communicate true, false, and uncertain CNNCS information, Researchers extended CNNCS by introducing Neutrosophic Confidence Cubic Sets (NCCSs). They also created a GDM model in the SVN multi-valued environment by employing an exponential similarity measure of NCCSs[12], [13].

Slope stability issues are not evaluated or classified with stable, unstable/failed, and quasi-stable statuses (multiple classification forms) by any of the current classification/evaluation methods, nor do they consider the multiple sampling data of each slope or the thorough representation and processing of neutrosophic matrix information. As a result, the current body of research on neutrosophic clustering/classification and slope stability evaluation techniques reflects their study gaps and deficiencies. In neutrosophic matrix situations, a more practical and efficient analysis technique must be created to bridge the gaps of numerous classification difficulties using the multi-point sample data of continuous slopes.

The NCCSs are first introduced in this study. Next, we used NCCSs and its score function in the MCDM scenario to create a decision matrix. To demonstrate the impact and logic of the suggested model in the complete NCCSs context, a sensitivity analysis is included, along with a real-world education case study[14], [15].

The study's salient features are listed below.

- To handle the numerous sample data for every slope, neutrosophic confidence cubic sets (NCCS) are suggested to overcome the uncertainty and vague information.
- To rank the alternatives the MOOSRA method is used under the neutrosophic set.
- Six criteria and six alternatives are used in this study.
- Sensitivity analysis is conducted to show

**Literature Review**

A crucial method for ensuring that sample data fall inside the confidence interval at a given probability distribution and confidence level is probability estimation of small sample data, which demonstrates its benefits in real-world engineering applications. A single-valued neutrosophic multivalued set (SvNMVS) is then formed by Ye et al. [16] as their assessed information after several experts assign a number of true, false, and indeterminate fuzzy values to the evaluation values of each alternative over various attributes in relation to a group decision-making (GDM) problem in the context of indeterminacy and inconsistency.

Using the exponential similarity measure of NCCSs in the case of SvNMVSs, they proposed a conversion technique from SvNMVS to a neutrosophic confidence cubic set (NCCS) and a GDM model to guarantee a certain degree of confidence in the evaluation values in the case of SvNMVSs and GDM reliability. To define NCCS, we first define SvNMVS in terms of the average values and confidence intervals of true, false, and indeterminate fuzzy sequences, according to the normal distribution and confidence level criteria. Subsequently, they introduced the NCCSs' exponential similarity metric, as well as their weighted exponential similarity metric and attributes.

Third, the weighted exponential similarity measure of NCCSs in the context of SvNMVSs is used to create a GDM model. Fourth, to demonstrate the created GDM model's applicability and usefulness in real-world GDM situations, it is applied to a choice scenario of landslide remediation schemes in the context of SvNMVSs. Subject to 90%, 95%, and 99% confidence levels, the created GDM model shows superiority over the current models in terms of choice flexibility and credibility/reliability.

One of the most important human innovations of the 20th century is the Internet. The Internet has had both positive and harmful effects on human society, just like past human innovations. To evaluate the drawbacks of the Internet, Gulistan et al. [13] proposed a novel idea known as N-neutrosophic cubic sets (NNCSs). A new idea of N-neutrosophic cubic sets (NNCSs) has been created by combining the concepts of N-cubic indeterminacy function and N-cubic falsity function with the N-cubic set. Compared to the N-cubic set, the N-neutrosophic cubic set (NNCS) offers a wider range of values to explore vagueness and uncertainty, which may be the reason for its originality.

The following parts introduce the remainder of this work. Some NCCS preliminary information is included in Section 2. Also, we show steps of the proposed MCDM method to compute the criteria weights and ranking the alternatives. To demonstrate the rationality and effectiveness of the suggested model in the NCC scenario, the constructed case study is provided in Section 3. Section 4 shows the results of the sensitivity analysis. Section 5 shows the conclusion of this study.

## 2. Neutrosophic confidence cubic sets (NCCS)

The NCCS can be defined as[16], [17]:

$$D_{1p}=\left\{\left(\begin{matrix}[\overline{V}_{T1}(I_p,c_k),V_{T1}^{+}(I_p,c_k)],\\ [\overline{V}_{I1}(I_p,c_k),V_{I1}^{+}(I_p,c_k)],;(V_{T1}(c_k),V_{I1}(c_k),V_{F1}(c_k))\\ [\overline{V}_{F1}(I_p,c_k),V_{F1}^{+}(I_p,c_k)]\end{matrix}\right)\middle|I_p=\left[-s_{\frac{p}{2}},s_{\frac{p}{2}}\right],c_k\in C\right\} \quad (1)$$

We can obtain the truth, indeterminacy, and falsity functions such as:

$$[\overline{V}_{T1}(I_p,c_k),V_{T1}^{+}(I_p,c_k)]=\left(\begin{matrix}[V_{T1k}+V_{T1k}I_p^{-},V_{T1k}+V_{T1k}I_p^{+}]=\\ \left[V_{T1k}-\frac{a_{T1k}}{\sqrt{r_k}}s_{\frac{p}{2}},V_{T1k}+\frac{a_{T1k}}{\sqrt{r_k}}s_{\frac{p}{2}}\right],\end{matrix}\right) \quad (2)$$

$$[\overline{V}_{I1}(I_p,c_k),V_{I1}^{+}(I_p,c_k)]=\left(\begin{matrix}[V_{I1k}+V_{I1k}I_p^{-},V_{I1k}+V_{I1k}I_p^{+}]=\\ \left[V_{I1k}-\frac{a_{I1k}}{\sqrt{r_k}}s_{\frac{p}{2}},V_{I1k}+\frac{a_{I1k}}{\sqrt{r_k}}s_{\frac{p}{2}}\right],\end{matrix}\right) \quad (3)$$

$$[\overline{V}_{F1}(I_p,c_k),V_{F1}^{+}(I_p,c_k)]=\left(\begin{matrix}[V_{F1k}+V_{F1k}I_p^{-},V_{F1k}+V_{F1k}I_p^{+}]=\\ \left[V_{F1k}-\frac{a_{F1k}}{\sqrt{r_k}}s_{\frac{p}{2}},V_{F1k}+\frac{a_{F1k}}{\sqrt{r_k}}s_{\frac{p}{2}}\right],\end{matrix}\right) \quad (4)$$

$$I_p=[I_p^{-},I_p^{+}]=\left[-s_{\frac{p}{2}},s_{\frac{p}{2}}\right] \quad (5)$$

$$V_{T1k}=\frac{1}{r_k}\sum_{p=1}^{r_k}V_{T1k,kp} \quad (6)$$

$$V_{I1k}=\frac{1}{r_k}\sum_{p=1}^{r_k}V_{I1k,kp} \quad (7)$$

$$V_{F1k}=\frac{1}{r_k}\sum_{p=1}^{r_k}V_{F1k,kp} \quad (8)$$

$$a_{T1k} = \sqrt{\frac{1}{r_k - 1}\sum_{p=1}^{r_k}\left(V_{T1,1p} - V_{T1k}\right)^2} \tag{9}$$

$$a_{I1k} = \sqrt{\frac{1}{r_k - 1}\sum_{p=1}^{r_k}\left(V_{I1,1p} - V_{i1k}\right)^2} \tag{10}$$

$$a_{F1k} = \sqrt{\frac{1}{r_k - 1}\sum_{p=1}^{r_k}\left(V_{F1,1p} - V_{F1k}\right)^2} \tag{11}$$

The assessment matrix is defined as:

$$H(x) = \begin{bmatrix} x_{11} & \cdots & x_{1s} \\ \vdots & \ddots & \vdots \\ x_{s1} & \cdots & x_{ss} \end{bmatrix} \tag{12}$$

$$= \begin{bmatrix} \left(\begin{pmatrix} [V_{T11}^-, V_{T11}^+], \\ [V_{I11}^-, V_{I11}^+], \\ [V_{F11}^-, V_{F11}^+] \end{pmatrix}, V_{T11}, V_{I11}, V_{F11}\right) & \cdots & \left(\begin{pmatrix} [V_{T1s}^-, V_{T1s}^+], \\ [V_{I1s}^-, V_{I1s}^+], \\ [V_{F1s}^-, V_{F1s}^+] \end{pmatrix}, V_{T1s}, V_{I1s}, V_{F1s}\right) \\ \vdots & \ddots & \vdots \\ \left(\begin{pmatrix} [V_{Ts1}^-, V_{Ts1}^+], \\ [V_{Is1}^-, V_{Is1}^+], \\ [V_{Fs1}^-, V_{Fs1}^+] \end{pmatrix}, V_{Ts1}, V_{Is1}, V_{Fs1}\right) & \cdots & \left(\begin{pmatrix} [V_{Tss}^-, V_{Tss}^+], \\ [V_{Iss}^-, V_{Iss}^+], \\ [V_{Fss}^-, V_{Fss}^+] \end{pmatrix}, V_{Tss}, V_{Iss}, V_{Fss}\right) \end{bmatrix} \tag{13}$$

$$H(V_{Tik}^-) = \begin{bmatrix} V_{T11}^- & \cdots & V_{T1s}^- \\ \vdots & \ddots & \vdots \\ V_{Ts1}^- & \cdots & V_{Tss}^- \end{bmatrix} \tag{14}$$

$$H(V_{Tik}^+) = \begin{bmatrix} V_{T11}^+ & \cdots & V_{T1s}^+ \\ \vdots & \ddots & \vdots \\ V_{Ts1}^+ & \cdots & V_{Tss}^+ \end{bmatrix} \tag{15}$$

$$H(V_{Tik}) = \begin{bmatrix} V_{T11} & \cdots & V_{T1s} \\ \vdots & \ddots & \vdots \\ V_{Ts1} & \cdots & V_{Tss} \end{bmatrix} \tag{16}$$

$$H(V_{Iik}^-) = \begin{bmatrix} V_{I11}^- & \cdots & V_{I1s}^- \\ \vdots & \ddots & \vdots \\ V_{Is1}^- & \cdots & V_{Iss}^- \end{bmatrix} \tag{17}$$

$$H(V_{Iik}^+) = \begin{bmatrix} V_{I11}^+ & \cdots & V_{I1s}^+ \\ \vdots & \ddots & \vdots \\ V_{Is1}^+ & \cdots & V_{Iss}^+ \end{bmatrix} \tag{18}$$

$$H(V_{Iik}) = \begin{bmatrix} V_{I11} & \cdots & V_{I1s} \\ \vdots & \ddots & \vdots \\ V_{Is1} & \cdots & V_{Fss} \end{bmatrix} \tag{19}$$

$$H(V_{Fik}^{-}) = \begin{bmatrix} V_{F11}^{-} & \cdots & V_{F1s}^{-} \\ \vdots & \ddots & \vdots \\ V_{Fs1}^{-} & \cdots & V_{Fss}^{-} \end{bmatrix} \quad (20)$$

$$H(V_{Fik}^{+}) = \begin{bmatrix} V_{F11}^{+} & \cdots & V_{F1s}^{+} \\ \vdots & \ddots & \vdots \\ V_{Fs1}^{+} & \cdots & V_{Fss}^{+} \end{bmatrix} \quad (21)$$

$$H(V_{Fik}) = \begin{bmatrix} V_{F11} & \cdots & V_{F1s} \\ \vdots & \ddots & \vdots \\ V_{Fs1} & \cdots & V_{Fss} \end{bmatrix} \quad (22)$$

## 3. The MOOSRA Method

We show the steps of the MOOSRA Method to compute the rank of the alternatives. The average method is used to compute the criteria weights.

Among the multi-objective optimization techniques is the MOOSRA approach. When the MOOSRA and MOORA methods are compared, the MOOSRA technique is less sensitive to significant fluctuations in the criterion values and does not exhibit the negative performance scores of the MOORA approach. It was utilized to create a multi-criteria decision-making framework for choosing the best cutting fluid for a gear process out of three different types, choosing material, and determining the ideal cutting parameters on surface roughness.

The MOORA approach and the MOOSRA method have comparable application steps. Specifically, the problem's decision matrix is constructed in the first stage, and the decision matrix is then normalized in the second. The MOOSRA technique uses a simple ratio of the sum of the normalized performance values for advantageous criteria to the sum of the normalized performance values for non-beneficial criteria to determine the overall performance score of each alternative.

The normalized decision matrix is computed

$$q_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (23)$$

The weighted decision matrix is computed

$$u_{ij} = w_j q_{ij} \quad (24)$$

Compute the final value of each alternative

$$H_{ij} = \frac{\sum_{j=1}^{g} u_{ij}}{\sum_{g+1}^{n} u_{ij}} \quad (25)$$

Rank the alternatives.

## 4. Numerical Example

This section shows the results of the proposed approach. We use six criteria as: Ideological Comprehension, Value Internalization, Leadership Development, Civic Responsibility, Organizational Participation, Innovative Engagement. We use six alternatives such as: Themed Political Lectures, Campus Cultural Festivals, Volunteer Service Campaigns, Digital Ideological Platforms, Student Peer Mentoring Groups, Community Integration Projects. Four experts have created the decision matrix using the NCCS as shown in Table 1.

Table 1. The NCCS.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
|---|---|---|---|---|---|---|
| $A_1$ | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) |
| $A_2$ | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) |
| $A_3$ | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) |
| $A_4$ | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) |
| $A_5$ | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) |
| $A_6$ | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) |
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) |
| $A_2$ | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) |
| $A_3$ | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) |
| $A_4$ | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) |
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| $A_6$ | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) |
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |
| $A_1$ | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) |
| $A_2$ | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) |
| $A_3$ | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) |
| $A_4$ | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) |
| $A_5$ | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) |
| $A_6$ | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) |
| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ |

| | | | | | | |
|---|---|---|---|---|---|---|
| A1 | ([0.74,0.82],[0.051,0.34],[0.0462,0.42],(0.75,0.20,0.23)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) |
| A2 | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.75,0.79],[0.18,0.24],[0.17,0.28],(0.78,0.18,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) |
| A3 | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) |
| A4 | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.8,0.8],[0.13,0.19],[0.15,0.21],(0.80,0.16,0.18)) | ([0.57,0.65],[0.07,0.22],[0.12,0.20],(0.61,0.15,0.11)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) |
| A5 | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) |
| A6 | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) | ([0.71,0.85],[0.14,0.28],[0.10,0.19],(0.78,0.21,0.15)) | ([0.6,0.6],[0.1118,0.2215],[0.1059,0.1608],(0.6,0.1667,0.1333)) | ([0.56,0.79],[0.06,0.29],[0.12,0.27],(0.68,0.18,0.20)) |

Then we obtain the weights of criteria using the average method as: C1= 0.16637547, C2= 0.16680938, C3= 0.165645516, C4= 0.168533072, C5= 0.166723844, C6= 0.165912718.

The weights are evenly distributed, ranging between 16.56% and 16.85%, which implies that all six criteria are considered nearly equally important.

The slight differences in weight could reflect nuances in priority, with U4 and U2 being slightly more emphasized.

Such a distribution is common in balanced decision frameworks, where no single criterion is allowed to dominate disproportionately.

- C1 (0.1664): Moderately significant, slightly below the average weight.
- C2 (0.1668): Slightly higher importance, indicating strong relevance.
- C3 (0.1656): Slightly lower weight, showing lesser but notable influence.
- C4 (0.1685): Highest weight, indicating the most influential criterion.
- C5 (0.1667): Close to C2, denoting consistent importance.
- C6 (0.1659): Moderately important, slightly below the average

The normalized decision matrix is computed using eq. (23) as shown in Fig 1.

The weighted decision matrix is computed using eq. (24) as shown in Fig 2.

Compute the final value of each alternative using eq. (25) as shown in Fig 3.

Rank the alternatives as shown in Fig 4.

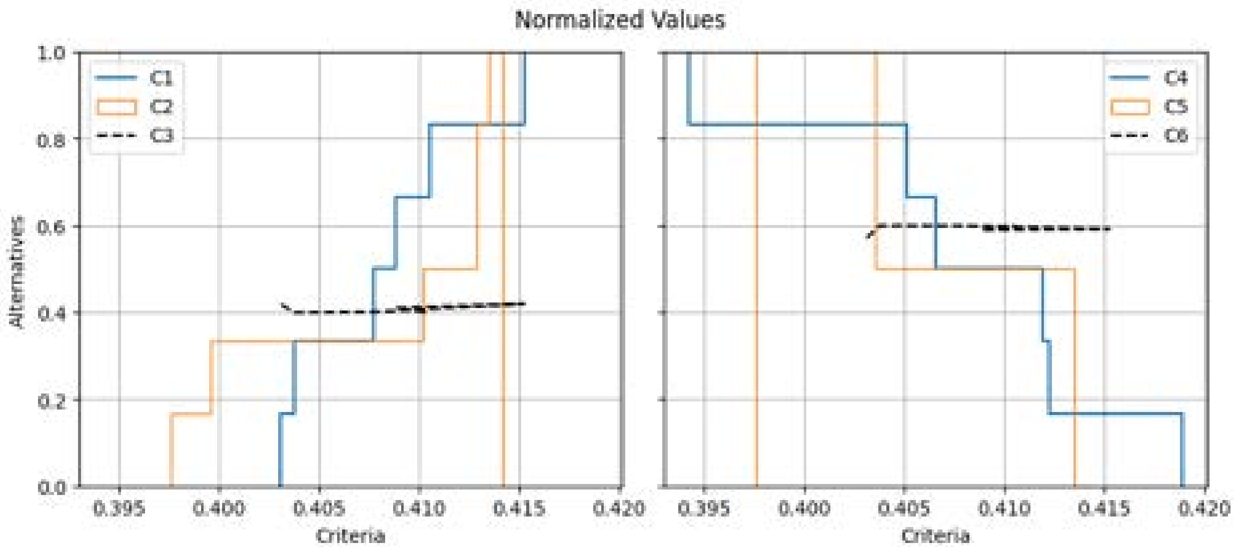


Fig 1. The normalized decision matrix.

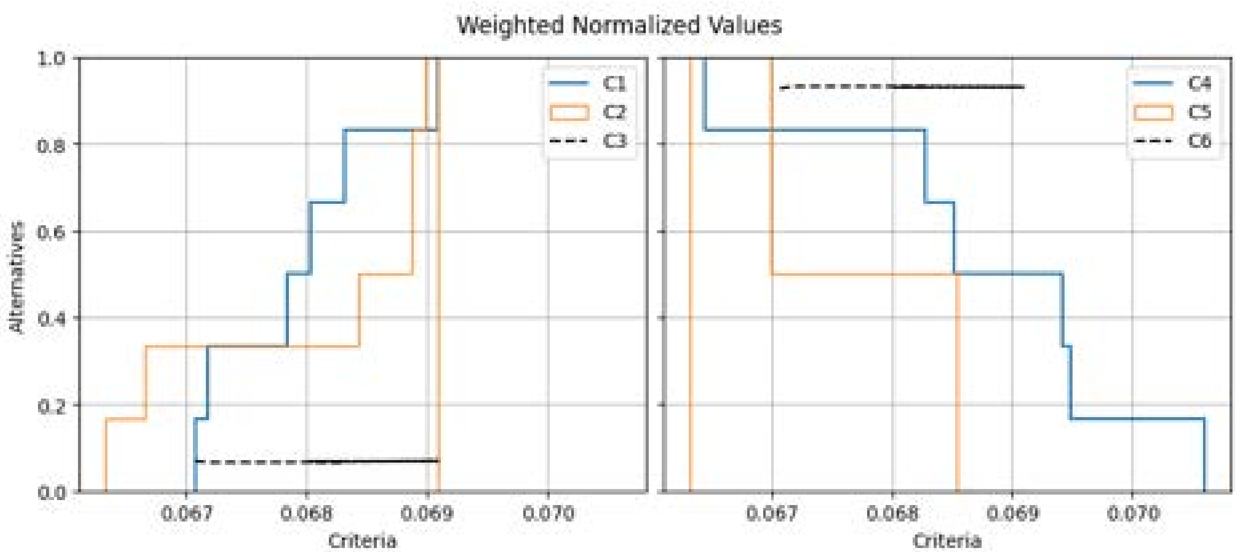


Fig 2. The weighted decision matrix.

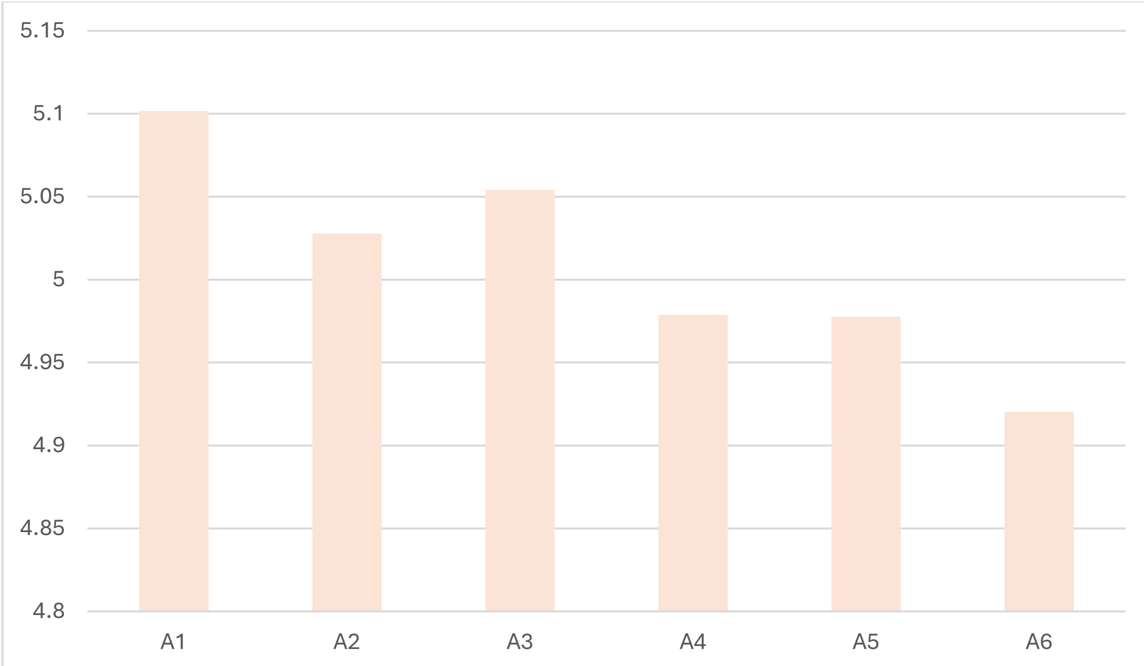


Fig 3. The final value of each alternative.

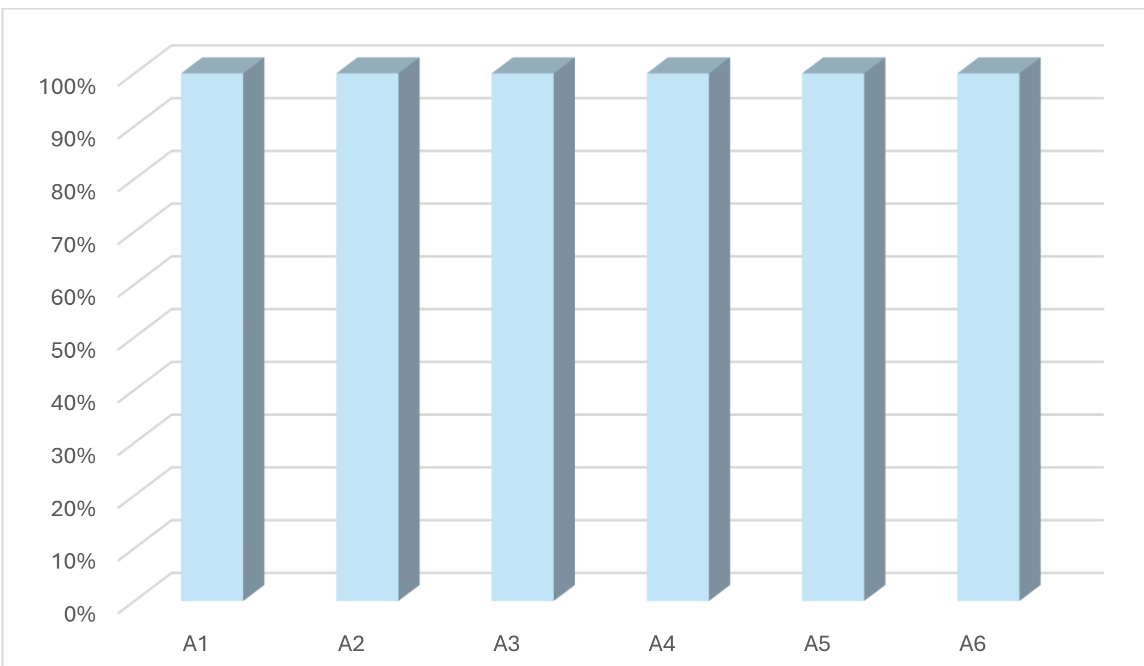


Fig 4. Rank of alternatives.

## 5. Sensitivity Analysis

This section shows the sanctity analysis. We change the criteria weights by ten cases as:

The weights assigned to six evaluation criteria across ten distinct scenarios (cases). Each weight reflects the relative importance of a particular criterion in the context of decision-making—commonly used in MCDM methods like MOOSRA.

- (Weight 1 to Weight 6): These represent six evaluation criteria (C1 to C6). The weights assigned indicate how critical each criterion is within each decision scenario.
- (Case 1 to Case 10): Each row represents a unique scenario, experiment, or evaluation case—where the weight distribution may vary slightly depending on the context or model sensitivity.
- The values hover around 0.166, indicating that all six criteria are nearly equally important in most cases. This balance suggests a uniform prioritization, though small variations reflect nuanced adjustments in emphasis.
- Highest weight observed: 0.1685
- Lowest weight observed: 0.1655
- The weight range is narrow, highlighting a stable and balanced evaluation environment.

Then we apply the steps of the MOOSRA method to rank the alternatives. Fig 5 shows the different scores of each alternative. Fig 6 shows the results of the sensitivity analysis.

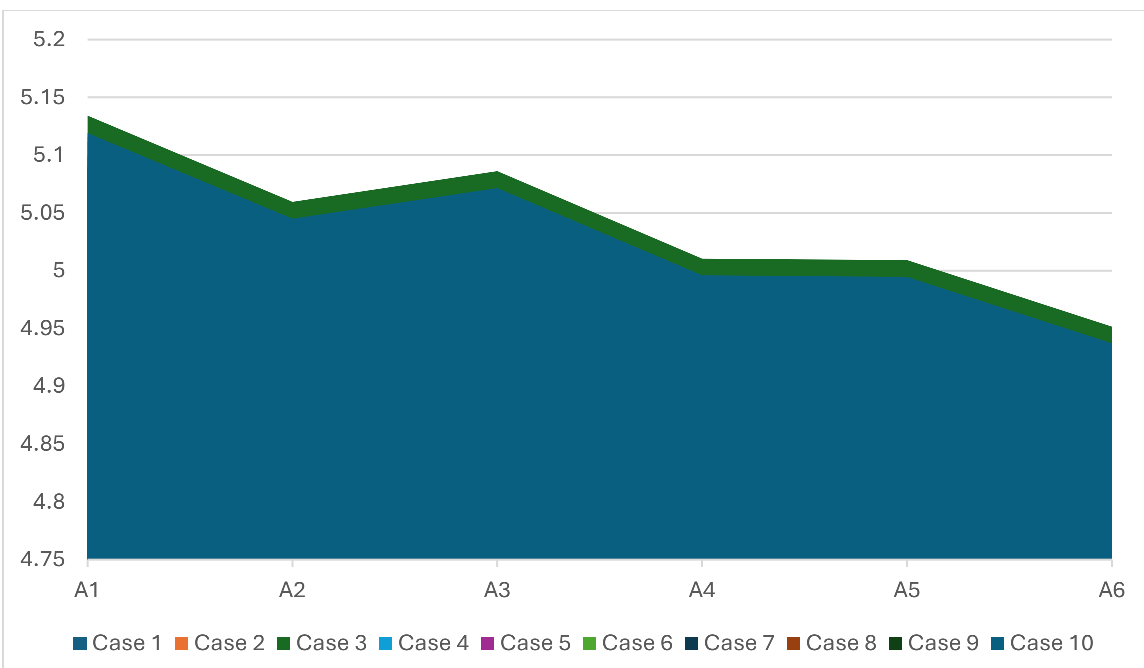


Fig 5. Different scores of each alternative.

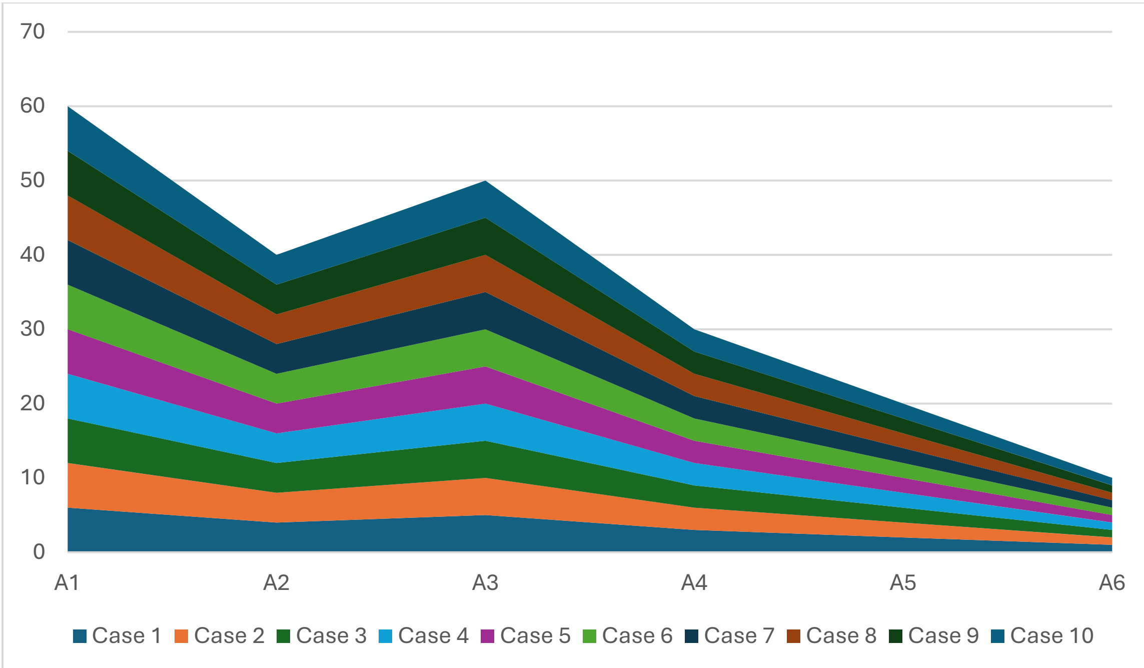


Fig 6. The ranks of alternatives.

Fig 6 represents the ranking results of six alternatives (A1–A6) across 10 different cases or evaluation scenarios (Case 1 to Case 10). Each value indicates the rank of an alternative in the corresponding case, where a lower rank number denotes better performance or higher preference.

- A1: Rank = 6 in all cases: A1 consistently ranks the lowest, indicating it is the least preferred or least effective alternative across all scenarios.
- A2: Rank = 4 in all cases: A2 holds a mid-lower position, showing moderate performance, but not among the top three.
- A3: Rank = 5 in all cases: A3 is also on the lower end, slightly better than A1 but worse than A2.
- A4: Rank = 3 in all cases: A4 ranks in the middle, suggesting it's a reasonably strong alternative.
- A5: Rank = 2 in all cases: A5 consistently performs very well, always in second place, reflecting high effectiveness or preference.
- A6: Rank = 1 in all cases: A6 is the top-performing alternative in every case, making it the most favored or successful choice in the evaluations.
- The rankings are uniform and stable across all cases, suggesting that the evaluation method is highly consistent, and that alternative performance does not fluctuate with different criteria weightings or scenarios.

- A6 is the most optimal, followed by A5 and A4, while A1 is the least preferred

**Comparative Analysis**

We compare the MCDM approach with the different methods to show the effectiveness of the proposed approach. We use the weights of the proposed approach to compare the proposed approach by different MCDM methods.

- A6 – Consistently Best Performer
  - Ranked 1st across all six methods.
  - Indicates strong dominance and agreement in performance.
  - Represents the most effective or ideal alternative under all evaluation strategies.
- A5 – Strong Contender
  - Always ranked 2nd, except under EDAS (rank 3).
  - Displays high reliability and consistently superior performance.
  - Very close to the top alternative, particularly under decision-making environments with slight preference variability.
- A4 – Mid-to-High Performer
  - Mostly ranked 3rd, except for a slight dip to 4th under VIKOR.
  - Shows steady mid-high placement, making it a reliable candidate in competitive scenarios.
- A2 – Middle Performer
  - Ranks mostly 4th, but drops to 3rd in VIKOR and 5th in MOORA.
  - Indicates variable performance depending on the method, suggesting sensitivity to specific criteria weighting or distance-based measures.
- A3 – Lower-Middle Performer
  - Ranks 5th in most methods, and 4th in MOORA.
  - Indicates it's outperformed by most, though it's better than the lowest option. Could be improved by tweaking key criteria inputs.
- A1 – Consistently Lowest Performer
  - Ranked 6th by all six methods.
  - Indicates unanimous agreement on underperformance.

- Suggests significant gaps in effectiveness relative to other alternatives.

| Rank | Frequency | Alternatives |
| --- | --- | --- |
| 1st | 6 | A6 |
| 2nd | 5 | A5 |
| 3rd | 4 | A4 |
| 4th | 3 | A2, A3 (depending on method) |
| 5th | 3 | A3 |
| 6th | 6 | A1 |

- High Agreement: Most methods show consistent rankings, especially for A6 and A1 (best and worst).
- Stable Methods: The methods used (Proposed, MABAC, TOPSIS, VIKOR, EDAS, MOORA) produce closely aligned results, supporting robustness.
- A6 is the optimal choice, while A1 needs considerable improvement.
- A2–A4 might be considered moderate choices depending on specific strategic goals or contextual constraints.

**5. Conclusions and Future Work**

This study presents a robust framework to evaluate the educational effectiveness of party-building activities in universities by focusing on measurable outcomes. By leveraging clearly defined criteria and evaluating distinct implementation models, it provides a foundation for enhancing the strategic planning of political education programs. The findings underline the importance of innovation, engagement, and value transmission in fostering political literacy and leadership among students. We use the MCDM approach to deal with different criteria. We used the MOOSRA methodology to rank the alternatives. The Neutrosophic confidence cubic sets (NCCS) to deal with uncertainty and vague information. The sensitivity analysis is conducted to show the stability of the ranks.

Future efforts should prioritize adaptive and student-centered approaches to ensure that party-building activities remain relevant, impactful, and aligned with the evolving educational landscape.

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**References**

[1] R. Yu, H. Mo, J. Liao, and Y. Wang, "Research and Practice on the Construction of Benchmark Faculties and Departments for Party Building Work in the Context of 'Three-Whole Education,'" in *SHS Web of Conferences*, EDP Sciences, 2024, p. 2006.

[2] L. Feng and J. Qiang, "Discussion on the Party Building Work in Colleges and Universities from the Perspective of" Rules of Law," 2019.

[3] Z. ZHONG, "Research on the Education and Training of College Student Party Members," *High. Educ. Soc. Sci.*, vol. 8, no. 1, pp. 98–102, 2015.

[4] Y. Gong, "Exploring the Path of Strengthening the Education and Management of Student Party Members in Colleges and Universities in the New Era," in *2021 2nd International Conference on Modern Education Management, Innovation and Entrepreneurship and Social Science (MEMIESS 2021)*, Atlantis Press, 2021, pp. 143–147.

[5] W. H. Wang, "The Coordinated Development of Party Construction Work and Campus Atmosphere Construction in Private Colleges and Universities," in *2018 International Conference on Advances in Social Sciences and Sustainable Development (ASSSD 2018)*, Atlantis Press, 2018, pp. 345–348.

[6] H. Xu, "Issues and Countermeasures of Student Party Branch Work in Higher Education under the Context of Integrated Education," *Open J. Soc. Sci.*, vol. 12, no. 12, pp. 406–414, 2024.

[7] C. Su, "The background significance and results combing of the research on the quality evaluation system of the party building work in colleges and universities in the new era," *J. High. Educ. Res.*, vol. 2, no. 4, pp. 178–185, 2021.

[8] S. Feng, "The Fit and Interaction between College Party Building and College Students' Ideological and Political Education," 2020.

[9] W. Yuting, "Study on the Synergistic Fusion of Work of Party Building and Ideological and Political Work in Local Colleges and Universities form the Perspective of 'Three-wide Education,'" *Acad. J. Humanit. Soc. Sci.*, vol. 6, no. 8, pp. 45–50, 2023.

[10] J. Zhan, M. Khan, M. Gulistan, and A. Ali, "Applications of neutrosophic cubic sets in multi-criteria decision-making," *Int. J. Uncertain. Quantif.*, vol. 7, no. 5, 2017.

[11] M. Ali, I. Deli, and F. Smarandache, "The theory of neutrosophic cubic sets and their applications in pattern recognition," *J. Intell. fuzzy Syst.*, vol. 30, no. 4, pp. 1957–1963, 2016.

[12] M. Gulistan and N. Hassan, "A generalized approach towards soft expert sets via neutrosophic cubic sets with applications in games," *Symmetry (Basel).*, vol. 11, no. 2, p.

289, 2019.

[13] M. Gulistan, A. Elmoasry, and N. Yaqoob, "N-version of the neutrosophic cubic set: application in the negative influences of Internet," *J. Supercomput.*, vol. 77, no. 10, pp. 11410–11431, 2021.

[14] S. Gomathi, M. Karpagadevi, S. Krishnaprakash, A. Revathy, and S. Broumi, "Cubic spherical neutrosophic sets for advanced decision-making," *Neutrosophic Sets Syst.*, vol. 73, no. 1, p. 24, 2024.

[15] S. Zhang and J. Ye, "Group decision-making model using the exponential similarity measure of confidence neutrosophic number cubic sets in a fuzzy multi-valued circumstance," *Neutrosophic Sets Syst.*, vol. 53, no. 1, p. 8, 2023.

[16] J. Ye, Z. Zhang, R. Yong, and S. Du, "MAGDM Model Using the Exponential Similarity Measure of Neutrosophic Confidence Cubic Sets in a Single-Valued Neutrosophic Multivalued Circumstance," *J. Math.*, vol. 2023, no. 1, p. 5150472, 2023.

[17] H. Wang, R. Yong, and J. Ye, "A slope stability classification model based on the matrix energy of neutrosophic confidence cubic sets for multi-point sampling data of slopes," *Expert Syst. Appl.*, vol. 266, p. 125801, 2025.

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