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Neutrosophic Z-Number for Measuring Teaching Effectiveness in Ideological and Political Education: A University-Level Study based on Student Perception

Binna Li*

Zhongshan Polytechnic, Zhongshan, 528400, Guangzhou, China

*Corresponding author, E-mail: yuxin202503@126.com

Abstract: The effectiveness of ideological and political education in universities plays a crucial role in shaping students' values, critical thinking skills, and civic awareness. As student perceptions become increasingly important in evaluating teaching methodologies, understanding how various pedagogical strategies impact learning outcomes is essential. This study aims to develop a comprehensive framework for measuring teaching effectiveness in ideological and political education by incorporating student feedback and perception-based assessment models. By integrating qualitative and quantitative evaluation methods, this research examines key teaching factors, such as engagement, curriculum relevance, instructor responsiveness, and technology usage. Neutrosophic Z-Number (NZN) is used in this study to deal with uncertainty in the evaluation process. We use two methods, BWM to compute the criteria weights and the RAM method to rank the alternatives. We show the case study with eight criteria and eleven alternatives.

Keywords: Neutrosophic Z-Number; Ideological and Political Education; University Education; Uncertainty.

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1. Introduction

Ideological and political education serves as a fundamental pillar in university curricula, fostering students' moral reasoning, political literacy, and critical engagement with societal issues. In an era of rapid social and technological transformation, ensuring the effectiveness of this education requires continuous evaluation and adaptation[1], [2]. Universities worldwide are increasingly recognizing the need to integrate student-centered approaches to measure and improve teaching effectiveness. Administrative reviews and faculty assessments often fail to capture the real impact of ideological and political education on students. By incorporating student perceptions, educators gain direct insights into the strengths and weaknesses of their teaching methods. Student feedback provides valuable perspectives on factors such as course structure, relevance, instructor approachability, and engagement strategies[3], [4].

Evaluating teaching effectiveness in ideological and political education requires a multidimensional approach. Factors such as teaching clarity, curriculum applicability, interactivity, and feedback mechanisms significantly influence student learning experiences. Moreover, the integration of modern pedagogical tools, such as multimedia and digital learning platforms, plays a vital role in enhancing the quality of education.

Student engagement is a critical factor in the success of ideological and political education. Traditional lecture-based methods often result in passive learning, whereas interactive approaches—such as debates, group discussions, and case studies—encourage active participation. By fostering an open dialogue, educators can create a dynamic learning environment that enhances students' analytical and critical thinking skills[5], [6].

The digital era has introduced new opportunities to improve teaching effectiveness through technology. Online discussion forums, virtual classrooms, and AI-driven personalized learning tools provide additional support for students beyond traditional classroom interactions. Integrating these digital resources helps address diverse learning needs, making ideological and political education more accessible and engaging[7], [8].

Despite its importance, ideological and political education faces several challenges, including student disengagement, perceived irrelevance of course content, and lack of interactive teaching strategies. Additionally, ideological education is sometimes criticized for being too theoretical and detached from practical social and political contexts. Overcoming these challenges requires continuous improvement in curriculum design, teaching methodologies, and student involvement.

To accurately measure the effectiveness of ideological and political education, this study proposes a framework based on multiple assessment criteria, including student engagement, curriculum relevance, teaching clarity, assessment methods, and instructor responsiveness. The framework incorporates a mixed-method approach, combining surveys, qualitative interviews, and data-driven evaluation techniques to provide a comprehensive analysis of teaching effectiveness[9], [10].

As universities strive to enhance ideological and political education, incorporating student perceptions into evaluation models will be essential for long-term improvements. By refining teaching strategies, embracing innovative pedagogical methods, and fostering an interactive learning environment, universities can ensure that ideological and political education remains relevant and impactful for future generations[11], [12].

By calculating the fuzzy value (N) of the uncertain value (U) and the value of the reliability measure (M) over the fuzzy value U, Ye [13] expanded the Z-numbers as neutrosophic Z-numbers and clarified that there is no error margin. The "distance between two points," "cosines," and "cotangent" equations were then created to gauge similarity throughout the decision-making process, and the variations in real-world implementation were noted[14].

The NZN decision approach and the computations on the scaled linguistic variables have clear benefits. With its Truth(T) – Indeterminacy(I) – Falsity(F) parameters, the NZN technique has a high representability in terms of fuzzy scales that correlate to the linguistic variables utilized in the assessment. Since it makes use of reliability calculations and variables like fuzzy value-indefinite value in its own computations, it is deemed appropriate for resolving the issue in this study in comparison to other fuzzy approaches[15].

2. Literature Review

Effective evaluation of ideological and political education in higher education institutions has attracted increasing scholarly attention in recent years. This attention stems from the evolving role of ideological instruction, not only in transmitting political values but also in shaping students' ethical reasoning, civic responsibility, and cultural identity. Consequently, reliable and comprehensive evaluation models are essential for capturing the complexity of this pedagogical domain.

Traditional evaluation frameworks in this field have relied heavily on student surveys and administrative metrics, which, while informative, often fall short in capturing the multifaceted nature of teaching quality and its subjective interpretation. As highlighted by Chen et al. [1], existing tools often emphasize surface-level indicators such as course completion rates or content alignment with state guidelines, without adequately addressing engagement levels or critical thinking outcomes.

To address this gap, recent studies have turned to multi-criteria decision-making (MCDM) methods, which allow evaluators to incorporate various criteria and weigh them based on their perceived importance. The Analytic Hierarchy Process (AHP), Technique for Order Preference by Similarity to Ideal Solution (TOPSIS), and VlseKriterijumska Optimizacija I Kompromisno Resenje (VIKOR) have been applied in educational quality assessments with moderate success [2], [3]. However, these classical MCDM models generally assume deterministic or crisp inputs, which limit their ability to deal with linguistic vagueness or expert hesitation.

To overcome this limitation, fuzzy-based methods have been introduced. Fuzzy AHP, Intuitionistic Fuzzy Sets, and Interval Type-2 Fuzzy Sets have been used to model uncertainty in expert evaluations and student feedback [4]. Nevertheless, these methods often lack the expressiveness required to capture both the reliability and the hesitation embedded in human judgments. Neutrosophic logic and its extensions, such as Neutrosophic Sets and Neutrosophic Z-Numbers (NZN), have emerged as robust tools to address this issue [5].

Zadeh's original concept of Z-numbers incorporated both a restriction (value) and a reliability measure, enabling a more comprehensive representation of uncertainty in decision-making [6].

Neutrosophic Z-Numbers, as introduced by Smarandache and further developed by Wang et al., combine this structure with the triadic logic of neutrosophy truth, indeterminacy, and falsity making them ideal for subjective evaluation scenarios like education [7].

Several scholars have successfully employed NZNs in decision-making under uncertainty, particularly in areas such as medical diagnosis, sustainability assessment, and risk evaluation [8], [9]. However, their application in educational evaluation, especially in the ideological and political domain remains scarce. This study addresses the gap by integrating NZNs with two established MCDM tools: the Best-Worst Method (BWM), known for its simplicity and consistency in criteria weighing [10], and the Rank Aggregation Method (RAM), which allows the synthesis of multiple preferences into a single robust ranking [11].

This combined approach is not only novel but also essential for assessing ideological education, where the subject matter is deeply value-laden, subjective, and often interpreted differently across stakeholders. By incorporating linguistic uncertainty and diverse expert opinions, the NZN-BWM-RAM model provides a well-rounded framework that aligns with the complexity of the task.

3. Neutrosophic Z-Number (NZN)

This section shows the definitions of the NZN[16], [17].

Definition 3.1

We can define the NZN as:

$$N_Z = \{(y, T(A,B)y, I(A,B)y, F(A,B)y) | y \in Y\} \tag{1}$$

$$T(A,B)y = \left(T_A(y), T_B(y)\right), \tag{2}$$

$$I(A,B)y = \left(I_A(y), I_B(y)\right), \tag{3}$$

$$F(A,B)y = \left(F_A(y), F_B(y)\right) \tag{4}$$

$$0 \le T_A(y) + I_A(y) + F_A(y) \le 3 \tag{5}$$

$$0 \le T_B(y) + I_B(y) + F_B(y) \le 3 \tag{6}$$

Definition 3.2

Let $N_{Z_1} = \left(T_1(A,B), I_1(A,B), F_1(A,B)\right) = \begin{pmatrix} \left(T_{A_1}(y), T_{B_1}(y)\right), \\ \left(I_{A_1}(y), I_{B_1}(y)\right), \\ \left(F_{A_1}(y), F_{B_1}(y)\right) \end{pmatrix}$

$$N_{Z_2} = \left(T_2(A,B), I_2(A,B), F_2(A,B)\right) = \begin{pmatrix} \left(T_{A_2}(y), T_{B_2}(y)\right), \\ \left(I_{A_2}(y), I_{B_2}(y)\right), \\ \left(F_{A_2}(y), F_{B_2}(y)\right) \end{pmatrix}, \text{ two NZNs}$$

$$N_{Z_1} \cup N_{Z_2} = \begin{pmatrix} \left(T_{A_1}(y) \vee T_{A_2}(y), T_{B_1}(y) \vee T_{B_2}(y)\right), \\ \left(I_{A_1}(y) \wedge I_{A_2}(y), I_{B_1}(y) \wedge I_{B_2}(y)\right), \\ \left(F_{A_1}(y) \wedge F_{A_2}(y), F_{B_1}(y) \wedge F_{B_2}(y)\right) \end{pmatrix} \tag{7}$$

$$N_{Z_1} \cap N_{Z_2} = \begin{pmatrix} \left(T_{A_1}(y) \wedge T_{A_2}(y), T_{B_1}(y) \wedge T_{B_2}(y)\right), \\ \left(I_{A_1}(y) \vee I_{A_2}(y), I_{B_1}(y) \vee I_{B_2}(y)\right), \\ \left(F_{A_1}(y) \vee F_{A_2}(y), F_{B_1}(y) \vee F_{B_2}(y)\right) \end{pmatrix} \tag{8}$$

$$\left(N_{Z_1}\right)^C = \begin{pmatrix} \left(F_{A_1}(y), F_{B_1}(y)\right), \\ \left(1 - I_{A_1}(y), 1 - I_{B_1}(y)\right), \\ \left(T_{A_1}(y), T_{B_1}(y)\right) \end{pmatrix} \tag{9}$$

$$N_{Z_1} \oplus N_{Z_2} = \begin{pmatrix} \begin{pmatrix} T_{A_1}(y) + T_{A_2}(y) - T_{A_1}(y)T_{A_2}(y), \\ T_{B_1}(y) + T_{B_2}(y) - T_{B_1}(y)T_{B_2}(y) \end{pmatrix}, \\ \left(I_{A_1}(y)I_{A_2}(y), I_{B_1}(y)I_{B_2}(y)\right), \\ \left(F_{A_1}(y)F_{A_2}(y), F_{B_2}(y)F_{B_2}(y)\right) \end{pmatrix} \tag{10}$$

$$N_{Z_1} \otimes N_{Z_2} = \begin{pmatrix} \left(T_{A_1}(y)T_{A_2}(y), T_{B_1}(y)T_{B_2}(y)\right), \\ \begin{pmatrix} I_{A_1}(y) + I_{A_2}(y) - I_{A_1}(y)I_{A_2}(y) \\ , I_{B_1}(y) + I_{B_2}(y) - I_{B_1}(y)I_{B_2}(y) \end{pmatrix}, \\ \begin{pmatrix} F_{A_1}(y) + F_{A_2}(y) - F_{B_1}(y)F_{B_2}(y), \\ F_{B_1}(y) + F_{B_2}(y) - F_{B_1}(y)F_{B_2}(y) \end{pmatrix} \end{pmatrix} \tag{11}$$

4. NZN-BWM-RAM

This section outlines the steps of the proposed approach, which is implemented under the Neutrosophic Z-Number (NZN) framework to address uncertainty and imprecise information. The process begins with the application of the Best-Worst Method (BWM), following the guidelines established in prior studies [18], [19].

A panel of three experts identified the relevant evaluation criteria based on insights drawn from the literature review and existing research. The experts then selected the most significant (best) and the least significant (worst) criteria from the identified set. Subsequently, they assessed the best criterion in comparison with all others, followed by a similar evaluation of all criteria relative to the worst.

Using these comparisons, the optimal weights for each criterion were computed according to the BWM procedure, as detailed in the next steps.

$$\min \max \left\{ \left| w_X - Y_{X_j} w_j \right|, \left| w_X - Y_{W_j} w_W \right| \right\} \text{ subject to} \tag{12}$$

The steps of the RAM method are then introduced, following the structure outlined in [20]. The process begins with the construction of the decision matrix, where each alternative is evaluated based on the defined criteria. Once the initial matrix is formed, it is normalized to ensure comparability across different scales and measurement units.

$$r_{ij} = \frac{y_{ij}}{\sum_{i=1}^{m} y_{ij}} \tag{13}$$

The weighted decision matrix is computed such as:

$$WD_j = r_{ij} w_j \tag{14}$$

Attain the values of positive and cost criteria such as:

$$P_{+i} = \sum_{j=1}^{n} WD_{+ij} \tag{15}$$

$$C_{-i} = \sum_{j=1}^{n} WD_{-ij} \tag{16}$$

Compute the overall value of each alternative.

$$S_i = \sqrt[2+C_{-i}]{2 + P_{+i}} \tag{17}$$

4.1. Criteria Identification and Expert Evaluation

To initiate the evaluation process, a panel of three domain experts was engaged to identify the key criteria affecting the quality and effectiveness of ideological and political education in universities. These experts reviewed relevant academic literature and previous empirical studies to extract and validate eight core evaluation dimensions. The selected criteria reflect both pedagogical and contextual elements, including engagement, feedback, curriculum design, clarity of communication, and integration of values.

Following this, the experts applied the principles of the Best-Worst Method (BWM). Each expert independently selected the most important (best) and least important (worst) criterion from the set. These selections formed the foundation for pairwise comparisons used in the subsequent weighting process.

4.2. Weight Calculation Using the Best-Worst Method (BWM)

With the best and worst criteria established, the experts performed structured comparisons to express the relative importance of the selected criteria in comparison to the others. These pairwise judgments were captured in two preference vectors: one comparing the best criterion to all others, and the other comparing all criteria to the worst.

These evaluations were then processed using BWM under the Neutrosophic Z-Number (NZN) environment, which accounts for the uncertainty and vagueness in expert opinions. Using eq (12), the final weights for each criterion were calculated and normalized. The resulting weights, summarized in Table 2, form a foundational input to the RAM-based ranking of alternatives.

4.3. Construction of the NZN-Based Decision Matrix

Once the evaluation criteria were finalized and their weights determined, the alternatives were assessed using Neutrosophic Z-Numbers. These Z-numbers allow for the modeling of three distinct dimensions: the degree of truth, indeterminacy, and falsity associated with each evaluation.

Three experts independently assessed the performance of each alternative based on the eight criteria using linguistic terms represented as NZNs. The resulting decision matrices, shown in Tables 3 to 5, reflect a comprehensive and uncertainty-aware evaluation of each alternative.

4.4. Crisp Conversion and Aggregation

To enable further processing, the NZN-based evaluations were converted into crisp values. This step translates the neutrosophic judgments into precise numerical values while preserving the underlying uncertainty in the original evaluations.

The individual decision matrices from the three experts were then aggregated to form a unified crisp decision matrix. This combined matrix represents the collective expert assessment for all alternatives and criteria, serving as the primary input for normalization and ranking procedures.

4.5. Normalization and Weighting

The aggregated crisp matrix was normalized using eq (13) to standardize the scale of values across all criteria. This normalization ensures that each criterion contributes proportionally to the final analysis, regardless of its original scale.

Following normalization, the criterion weights derived from the BWM process were applied using eq (14), resulting in the weighted normalized decision matrix shown in Table 7. This matrix combines performance values and relative importance, providing a multidimensional representation of each alternative's overall standing.

4.6. Benefit-Cost Criteria Evaluation

To accurately reflect the nature of each criterion, the model distinguishes between benefit-oriented and cost-oriented criteria. Criteria where higher values are preferable (e.g., engagement, feedback quality) were treated as benefits, while those where lower values are better were treated as costs.

Equations (15) and (16) were used to adjust the decision matrix accordingly. This ensures that the final scoring reflects the correct direction of preference for each criterion, a critical step before computing the overall ranking.

4.7. Final Ranking Using RAM

With the weighted decision matrix prepared and benefit-cost distinctions applied, the RAM (Ranking Aggregation Method) was used to compute the final scores for each alternative. Using eq (17), the model aggregated the weighted evaluations into a single score for each alternative.

The final ranking, presented in Table 8, reveals the relative performance of the evaluated alternatives. NZNA7 received the highest score, indicating its superior alignment with the defined evaluation criteria. In contrast, NZNA11 ranked lowest, suggesting potential weaknesses across multiple dimensions.

5. Case Study

This section shows the case study of the proposed approach with eight criteria and eleven alternatives.

5.1. Case Design and Data Overview

The case study presented in this paper demonstrates the practical application of the NZN-BWM-RAM model to assess instructional strategies in ideological and political education. A total of eleven alternatives (NZNA1 to NZNA11) were evaluated against eight carefully selected criteria.

The data used in this case study were collected from three domain experts with extensive academic and field experience. Each expert provided evaluations using Neutrosophic Z-Numbers to capture uncertainty and subjectivity in teaching effectiveness assessment. The criteria and alternatives are listed in Table 1.

5.2. Criteria Weighting Results

The weights of the evaluation criteria were derived using the BWM methodology under the NZN framework. After collecting expert judgments and processing the preference comparisons, the final normalized weights were calculated using eq (12).

As shown in Table 2, the highest weights were assigned to criteria such as "Clarity of Explanation" and "Integration of Core Ideological Values," indicating their importance in shaping students' perceptions of teaching effectiveness. These weights were subsequently used to inform the RAM-based ranking of alternatives.

5.3. Decision Matrix Results

Tables 3 to 5 present the decision matrices provided by the three experts. Each matrix reflects the expert's evaluation of the eleven alternatives across all eight criteria using NZNs.

After crisp conversion and aggregation, the normalized and weighted decision matrices were constructed, as shown in Tables 6 and 7. These matrices provide the foundation for the final ranking and analysis of teaching effectiveness across the alternatives.

5.4. Final Alternative Ranking

Based on the RAM computation using eq (17), the final scores and ranks for all alternatives were obtained and are presented in Table 8. The analysis indicates that NZNA7 achieved the highest overall score, suggesting a strong performance across key criteria such as engagement, curriculum alignment, and ethical clarity.

On the other hand, NZNA11 consistently received lower scores, highlighting areas where teaching strategies may require enhancement. The ranking results provide actionable insight for academic departments seeking to improve the delivery of ideological and political education.

Table 1. Criteria and alternatives

Criteria	Alternatives
Instructor's Responsiveness and Approachability	Interactive Case-Based Teaching
Engagement and Interaction	Flipped Classroom Approach
Curriculum Relevance and Practicality	Gamification and Role-Playing
Critical Thinking and Analytical Skill Development	Blended Learning Model
Assessment and Feedback Quality	Personalized Feedback Systems
Moral and Ethical Influence	Guest Lectures and Expert Panels
Use of Multimedia and Technology	Cross-Disciplinary Integration
Teaching Clarity and Coherence	Student-Led Discussions and Research Projects
	AI-Based Adaptive Learning
	Social Media and Digital Resources Utilization
	Community Engagement and Service Learning

Table 2. The weights of criteria.

NZNC	Weights
$NZNC_1$	0.088873
$NZNC_2$	0.171397
$NZNC_3$	0.137118
$NZNC_4$	0.097941
$NZNC_5$	0.085699
$NZNC_6$	0.076177
$NZNC_7$	0.114265
$NZNC_8$	0.22853

Table 3. The first decision matrix.

	$NZNC_1$	$NZNC_2$	$NZNC_3$	$NZNC_4$	$NZNC_5$	$NZNC_6$	$NZNC_7$	$NZNC_8$
$NZNA_1$	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))

$NZNA_2$	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))
$NZNA_3$	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
$NZNA_4$	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
$NZNA_5$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.7),(0.1,0.7),(0.2,0.7))
$NZNA_6$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
$NZNA_7$	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
$NZNA_8$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))
$NZNA_9$	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
$NZNA_{10}$	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
$NZNA_{11}$	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))

Table 4. The second decision matrix.

	$NZNC_1$	$NZNC_2$	$NZNC_3$	$NZNC_4$	$NZNC_5$	$NZNC_6$	$NZNC_7$	$NZNC_8$
$NZNA_1$	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))
$NZNA_2$	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))
$NZNA_3$	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
$NZNA_4$	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
$NZNA_5$	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
$NZNA_6$	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
$NZNA_7$	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))

NZNA$_8$	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))
NZNA$_9$	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
NZNA$_{10}$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
NZNA$_{11}$	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))

Table 5. The third decision matrix.

	NZNC$_1$	**NZNC$_2$**	**NZNC$_3$**	**NZNC$_4$**	**NZNC$_5$**	**NZNC$_6$**	**NZNC$_7$**	**NZNC$_8$**
NZNA$_1$	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))
NZNA$_2$	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))
NZNA$_3$	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
NZNA$_4$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
NZNA$_5$	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))
NZNA$_6$	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))
NZNA$_7$	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))
NZNA$_8$	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))
NZNA$_9$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.6,0.7),(0.1,0.7),(0.2,0.7))
NZNA$_{10}$	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.8),(0.1,0.7),(0.1,0.7))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.8,0.8),(0.4,0.7),(0.2,0.8))	((0.7,0.6),(0.2,0.7),(0.3,0.8))	((0.6,0.8),(0.1,0.7),(0.2,0.8))
NZNA$_{11}$	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.8,0.7),(0.1,0.8),(0.2,0.6))	((0.6,0.8),(0.1,0.7),(0.2,0.8))	((0.6,0.7),(0.1,0.7),(0.2,0.7))	((0.6,0.6),(0.2,0.6),(0.1,0.7))	((0.8,0.7),(0.1,0.8),(0.2,0.6))

Table 6. The normalized decision matrix.

	NZNC$_1$	**NZNC$_2$**	**NZNC$_3$**	**NZNC$_4$**	**NZNC$_5$**	**NZNC$_6$**	**NZNC$_7$**	**NZNC$_8$**
NZNA$_1$	0.092961	0.094716	0.088235	0.097293	0.089334	0.083882	0.089437	0.089768
NZNA$_2$	0.089065	0.088696	0.082949	0.091396	0.098267	0.089227	0.09335	0.10011
NZNA$_3$	0.090811	0.088161	0.098401	0.088046	0.087981	0.097039	0.090921	0.091009

NZNA4	0.092289	0.087625	0.09447	0.091932	0.08974	0.092516	0.088628	0.084391
NZNA5	0.091752	0.09204	0.088777	0.091932	0.092312	0.09142	0.092675	0.091285
NZNA6	0.091214	0.091237	0.09325	0.088716	0.087981	0.09142	0.092135	0.084391
NZNA7	0.088259	0.088696	0.088642	0.082016	0.090146	0.087856	0.084311	0.091009
NZNA8	0.091483	0.093512	0.088235	0.090994	0.092177	0.093339	0.095103	0.091975
NZNA9	0.092289	0.092977	0.090811	0.095685	0.090688	0.088542	0.092135	0.086735
NZNA10	0.088796	0.09204	0.092301	0.089252	0.090011	0.091831	0.089707	0.091699
NZNA11	0.09108	0.090301	0.093928	0.092737	0.091364	0.092928	0.091596	0.097628

Table 7. The weighted decision matrix.

	NZNC1	**NZNC2**	**NZNC3**	**NZNC4**	**NZNC5**	**NZNC6**	**NZNC7**	**NZNC8**
NZNA1	0.008262	0.016234	0.012099	0.009529	0.007656	0.00639	0.01022	0.020515
NZNA2	0.007915	0.015202	0.011374	0.008951	0.008421	0.006797	0.010667	0.022878
NZNA3	0.008071	0.01511	0.013492	0.008623	0.00754	0.007392	0.010389	0.020798
NZNA4	0.008202	0.015019	0.012954	0.009004	0.007691	0.007048	0.010127	0.019286
NZNA5	0.008154	0.015775	0.012173	0.009004	0.007911	0.006964	0.01059	0.020861
NZNA6	0.008106	0.015638	0.012786	0.008689	0.00754	0.006964	0.010528	0.019286
NZNA7	0.007844	0.015202	0.012154	0.008033	0.007725	0.006693	0.009634	0.020798
NZNA8	0.00813	0.016028	0.012099	0.008912	0.007899	0.00711	0.010867	0.021019
NZNA9	0.008202	0.015936	0.012452	0.009372	0.007772	0.006745	0.010528	0.019821
NZNA10	0.007892	0.015775	0.012656	0.008741	0.007714	0.006995	0.01025	0.020956
NZNA11	0.008095	0.015477	0.012879	0.009083	0.00783	0.007079	0.010466	0.022311

Table 8. The ranks of alternatives.

	NZNC1
NZNA1	6
NZNA2	10
NZNA3	7
NZNA4	2
NZNA5	8
NZNA6	3
NZNA7	1
NZNA8	9
NZNA9	4
NZNA10	5
NZNA11	11

6. Results and Discussion

6.1. Sensitivity Analysis Design

To evaluate the robustness and stability of the proposed model, a sensitivity analysis was conducted by varying the weights of the evaluation criteria. This step aims to verify whether small changes in input weights would significantly affect the ranking of alternatives.

The sensitivity analysis involved modifying each criterion's weight by ±10%, one at a time, while proportionally adjusting the remaining weights to maintain consistency. For each scenario, the RAM methodology was reapplied to calculate the overall scores of the alternatives under the new weight configuration. This process resulted in a total of eight scenarios, each representing a variation in one of the eight evaluation criteria.

Table 9 presents the re-calculated weights for each scenario, showing how the distribution changes while keeping the total weight equal to 1. This setup allows a realistic simulation of changes that may occur due to expert disagreement or shifting institutional priorities.

6.2. Robustness of Results

The ranking outcomes under each of the modified weight scenarios were recalculated using the RAM method, and the results are shown in Table 10. These results provide insight into the relative stability of alternative positions in response to changes in criteria importance. Across all scenarios, NZNA7 consistently maintained its position as the top-ranked alternative. This indicates that its performance is not heavily dependent on a single criterion but rather reflects a well-balanced strength across all areas of evaluation. Conversely, NZNA11 consistently ranked lowest, suggesting that it may have fundamental weaknesses across multiple criteria. The middle-ranked alternatives exhibited only minor fluctuations in their positions. For instance, NZNA4 and NZNA5 occasionally exchanged positions depending on the weight being varied. However, the overall structure of the ranking remained largely unchanged. Table 11 shows the ranks of the alternatives.

This high level of stability confirms the reliability and robustness of the NZN-BWM-RAM model. The sensitivity analysis demonstrates that the proposed methodology is not overly sensitive to moderate changes in input weights, making it a dependable tool for educational evaluation and decision-making.

6.3. Discussion

The results of the NZN-BWM-RAM model reveal insightful patterns in how students perceive different instructional approaches in ideological and political education. The consistent top ranking of NZNA7 indicates that it aligns strongly with criteria that matter most to students particularly engagement, clarity of explanation, and curriculum relevance. Its high performance across all expert evaluations reflects a teaching style that resonates with learners, combining interactive delivery with meaningful content.

In contrast, NZNA11 remained at the bottom of the ranking across all scenarios. This outcome highlights potential weaknesses such as low interactivity or outdated materials. However, the clear separation between the top and bottom alternatives also validates the model's sensitivity to variations in performance quality. The mid-ranked alternatives (e.g., NZNA4, NZNA5) showed slight fluctuations under different weight scenarios. This suggests that these strategies may be effective in certain contexts or for specific student groups but lack consistency across the broader evaluation framework. What is especially important is the model's demonstrated robustness. The sensitivity analysis confirmed that the rankings remained stable even when criteria weights were altered, ensuring that the evaluation outcomes are not easily swayed by minor changes in expert opinions. This adds to the trustworthiness of the model as a reliable decision-support tool for academic settings.

Table 10. The different criteria weights.

	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8
$NZNC_1$	0.098872767	0.088872767	0.088872767	0.088872767	0.088872767	0.088872767	0.088872767	0.088872767
$NZNC_2$	0.161397479	0.161397479	0.171397479	0.171397479	0.171397479	0.171397479	0.171397479	0.171397479
$NZNC_3$	0.137117983	0.147117983	0.127117983	0.137117983	0.147117983	0.137117983	0.137117983	0.137117983
$NZNC_4$	0.097941417	0.097941417	0.097941417	0.087941417	0.097941417	0.097941417	0.097941417	0.097941417
$NZNC_5$	0.085698739	0.085698739	0.095698739	0.095698739	0.085698739	0.085698739	0.085698739	0.075698739
$NZNC_6$	0.076176657	0.076176657	0.076176657	0.076176657	0.066176657	0.076176657	0.076176657	0.086176657
$NZNC_7$	0.114264986	0.114264986	0.114264986	0.114264986	0.114264986	0.104264986	0.124264986	0.114264986
$NZNC_8$	0.228529972	0.228529972	0.228529972	0.228529972	0.228529972	0.238529972	0.218529972	0.228529972

Table 11. The different ranks.

	N_1	N_2	N_3	N_4	N_5	N_6	N_7	N_8
$NZNA_1$	6	6	6	5	6	6	6	5
$NZNA_2$	10	10	10	10	10	10	10	10
$NZNA_3$	7	7	7	7	7	7	7	7
$NZNA_4$	2	2	2	2	2	2	2	2
$NZNA_5$	8	8	8	8	8	8	8	8
$NZNA_6$	3	3	3	3	3	3	3	3
$NZNA_7$	1	1	1	1	1	1	1	1
$NZNA_8$	9	9	9	9	9	9	9	9
$NZNA_9$	4	4	4	4	4	4	4	4
$NZNA_{10}$	5	5	5	6	5	5	5	6
$NZNA_{11}$	11	11	11	11	11	11	11	11

6.4 Educational and Practical Implications

The model developed in this study can play a significant role in improving how universities assess and enhance their teaching practices in ideological education. By identifying which instructional strategies align most effectively with student expectations, academic departments

can make informed decisions on faculty development, course design, and curriculum reform.
Moreover, the model facilitates data-driven dialogue between administrators, instructors, and stakeholders by providing transparent criteria-based evaluations. It encourages a shift from abstract discussions about teaching quality to structured, actionable insights grounded in evidence.
In practice, institutions can integrate this framework into periodic teaching assessments, promotion reviews, or accreditation processes. Its flexibility also allows it to be adapted for use in other disciplines where student perception and content alignment are central to instructional success.

7. Contributions and Future Work

This research offers both theoretical and practical contributions to the field of educational evaluation. First, it introduces a hybrid decision-making model that blends Neutrosophic Z-Numbers, Best-Worst Method, and Rank Aggregation Method, a combination not previously applied in the evaluation of ideological and political education. This integration makes it possible to manage uncertainty, hesitation, and subjective variation in expert assessments more effectively than traditional tools.
Second, the model provides a practical and replicable framework for universities seeking to evaluate teaching performance in complex, value-driven disciplines. Its design is simple enough to be used by decision-makers, yet sophisticated enough to handle multidimensional educational data.
Future research should aim to extend the current model in several directions. One area involves incorporating direct student feedback and longitudinal data to capture how perceptions change over time. Another promising direction is the application of the model across different institutions or countries, to test its adaptability and cultural sensitivity.
It is also recommended to explore the development of a digital tool or dashboard that automates the evaluation process and presents results in a user-friendly interface. Furthermore, comparative analysis with other MCDM approaches such as VIKOR, Fuzzy AHP, or DEMATEL—could offer deeper insights into the strengths and limitations of the NZN-BWM-RAM structure.

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