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q-Rung Orthopair Neutrosophic Soft Sets for Teaching Reform and Practice Efficiency of College Ideological and Political Courses under the Background of Digital Education

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Abstract: Higher education institutions are currently investigating novel approaches to improve practical effectiveness and teaching reform of Ideological and Political courses in the age of digital change. This study assesses reform strategies based on six main factors, such as platform usability, engagement levels, and integration of digital tools. This study uses a comparative assessment technique to examine the efficacy of eight novel options, ranging from VR-based training to smart classrooms. This study uses the uncertainty framework to overcome uncertainty under q-Rung Orthopair Neutrosophic Soft Sets. The results of data collected from colleges implementing digital teaching reforms highlight how digital education has the capacity to revolutionize I&P instruction. The research provides a methodical framework for maximizing the dissemination of ideological material and bringing educational principles into line with the demands of contemporary technology.

Keywords: Q-Rung Orthopair Neutrosophic Soft Sets; Teaching Reform; College Ideological and Political Courses; Background of Digital Education.

1. Introduction

In 1998, Smarandache [1] developed a novel mathematical technique using tripled MF in the [0,3] range. While fuzzy sets and all its extended structures either completely or partially ignore indeterminacy, this tool handles uncertainties more effectively by handling three different types of scenarios: independent, slightly independent, and dependent. In all the previously discussed fuzzy structures, membership degrees (MD) and non-membership degrees (NMD) are typically assessed using real values. However, to get around this restriction, Molodtsov [2] suggested soft sets since uncertainty problems are so complicated.

Compared to traditional fuzzy sets and their expansions, neutrophilic sets (NS) offer a more comprehensive understanding of uncertainty. Compared to standard fuzzy sets, Problems enhances the framework's capacity to manage uncertainty through indeterminate membership, which offers a more adaptable and efficient method of expressing complicated information. Neutrosophic sets easily handle the uncertainties in real-world scenarios and are well-suited for a variety of applications, including artificial intelligence and data miming. Several experts have proposed different methods for applying Neutrosophic Sets (NSs).

Real numbers are used in soft sets. Hussain et al. [3] introduced the innovative concept of Q-rung orthopair fuzzy soft sets. Despite the emphasis on MD and NMD in contemporary discourse, the degree of indeterminacy in object appraisal is commonly disregarded. This paper proposes a novel hybrid approach called q-RONSSs, which combines neutrosophic sets with q-ROF, to overcome this limitation. The distinctive feature of this approach is the inclusion of parameters that measure the degrees of truth, indeterminacy, and falsehood.

2. Literature Review

Yuan Li [4] built a conceptual model of the student participation mechanism through theoretical analysis and literature review, and it is based on the "Big Ideological and Political Course" concept. It also examines the theoretical underpinnings, current state, and difficulties of university students' involvement in college ideological and political education. The study first explores the origins and connotations of the "Big Ideological and Political Course" idea, contrasting the distinctions between traditional ideological and political education and the curriculum reform under the new concept. The present situation and deficiencies of university students' involvement in teaching are then examined.

He offered specific strategies and theoretical innovations to encourage university students' deep participation in college ideological and political education by examining avenues like policy innovation, curriculum design reform, teacher-student interaction mechanisms, and the use of information technology. This offers fresh viewpoints and useful insights into the reform of college ideological and political education.

People’s lives and jobs have changed drastically since the Internet age began, and society has advanced quickly thanks to its efficiency and ease. However, there are certain drawbacks to the Internet's openness and dispersion as well. These drawbacks are particularly noticeable when it comes to political and ideological instruction at colleges and universities. Students can develop a positive learning attitude, develop moral and ideological character, and be guided in establishing the right values and view on life through ideological and political education.

One of the biggest challenges facing colleges and universities today is how to implement innovative, effective ideological and political education in the network era and achieve the advancement of such education. The novel approaches to political and ideological teaching at colleges and universities throughout the network age are specifically examined by Gao et al. [5].

Ideologies, customs, culture, and values that inform economics, politics, morals, religions, information, reality, comparative and historical aesthetics, and artistic school knowledge are together referred to as education. The problematic qualities in political education include lack in information sharing, user's participatory experience, and incentive mechanism has become a crucial factor. The Deep Learning-Based Innovative Ideological Behavior Education Model (DL-IIBEM) has been presented by Li et al. [6] to improve the platform's performance, increase the mechanism to encourage information sharing, and improve the user's interactive experience. The average likelihood of completing social media tasks on a popular network, the anticipated utility degree for individual users, and the user feedback probability are all strengthened by integrating Knowledge Network Mechanism Analysis with DL-IIBEM. The platform has been significantly enhanced.

3. Preliminaries

In this section, we present the foundational mathematical concepts required for the proposed decision-making framework. These include the definitions of soft sets, neutrosophic sets, q-rung orthopair fuzzy sets, and q-rung orthopair neutrosophic soft sets. We also define essential evaluation functions such as score, accuracy, and certainty, which are crucial for ranking alternatives in uncertain environments [8].

3.1 Soft Set

Let U be an initial universal set and E a set of parameters. A soft set F over U with respect to parameters in E is defined as a mapping:

$$F: E \rightarrow \mathcal{P}(U)$$

where $\mathcal{P}(U)$ is the power set of U. For each $e \in E, F(e) \subseteq U$ represents the set of elements in U that satisfy the parameter e.

Example 3.1:

Let $U = \{u_1, u_2, u_3\}$ be a set of digital learning platforms, and $E =$ {interactive, accessible, affordable}.
A soft set F might be:

$F($ interactive $) = \{u_1, u_2\}$

$F($ accessible $) = \{u_2, u_3\}$

$F($ affordable $) = \{u_1\}$

4.2 Neutrosophic Set

Let X be a universe of discourse. A neutrosophic set A on X is defined as:

$$A = \{\langle x, T_A(x), I_A(x), F_A(x)\rangle : x \in X\}$$

where:

$T_A(x) \in [0,1]$: the degree of truth-membership.

$I_A(x) \in [0,1]$: the degree of indeterminacy-membership,

$F_A(x) \in [0,1]$: the degree of falsity-membership.

with the only constraint:

$$0 \leq T_A(x) + I_A(x) + F_A(x) \leq 3$$

Example 3.2:

Let $x = u_1$ be a learning platform, and suppose:

$T(u_1) = 0.7, I(u_1) = 0.2, F(u_1) = 0.1$

Then:

$$A = \{\langle u_1, 0.7,0.2,0.1\rangle\}$$

3.3 q -Rung Orthopair Fuzzy Set (q -ROFS)

A q-Rung Orthopair Fuzzy Set (q-ROFS) is a generalization of intuitionistic fuzzy sets, defined for a universe X as:

$$A = \{\langle x, \mu_A(x), \nu_A(x)\rangle : x \in X\}$$

with the constraint:

$$\mu_A(x)^q + \nu_A(x)^q \leq 1, \forall x \in X, q \in \mathbb{N}, q \geq 1$$

where:

$\mu_A(x)$: membership degree,

$\nu_A(x)$: non-membership degree.

Larger q allows more flexibility in representing uncertainty.

3.4 q -Rung Orthopair Neutrosophic Set (q -RONS)

A q-Rung Orthopair Neutrosophic Set ($q -$ RONS) is defined as:

$$A = \{\langle x, T(x), I(x), F(x)\rangle : x \in X\}$$

subject to the constraint:

$$T(x)^q + F(x)^q \leq 1, T(x), I(x), F(x) \in [0,1]$$

Note:
Unlike traditional neutrosophic sets, only the truth and falsity components are bound by the q-norm condition, giving more flexibility in modeling.

Example 3.3 (Valid q -RONS with q = 2):

Let $x = u_2$, and suppose:

$T = 0.6, I = 0.3, F = 0.5$

Then:

$$T^2 + F^2 = 0.36 + 0.25 = 0.61 \leq 1 \quad (\text{ valid })$$

3.5 q -Rung Orthopair Neutrosophic Soft Set (q-RONSS)

Let U be a universe and E a set of parameters. A q -Rung Orthopair Neutrosophic Soft Set is a function:

$$F: E \rightarrow \mathcal{P}(U \times [0,1]^3)$$

For each parameter $e \in E$, and $u \in U$, the function assigns a triple $(T_e(u), I_e(u), F_e(u))$ such that:

$$T_e(u)^q + F_e(u)^q \leq 1, T_e(u), I_e(u), F_e(u) \in [0,1]$$

3.6 Score, Accuracy, and Certainty Functions

Let $A = (T, I, F)$ be a q-RONS element. Then:

Score Function ([Smarandache, 2020]):

$$S(A) = \frac{2 + T - I - F}{3}$$

Accuracy Function:

$$A(A) = T - F$$

Certainty Function:

$$C(A) = T$$

These functions are used to evaluate and rank alternatives under uncertainty.
Example 3.4:

Let $A = (0.8, 0.1, 0.3)$, then:

$$S = \frac{2 + 0.8 - 0.1 - 0.3}{3} = \frac{2.4}{3} = 0.80$$
$$A = 0.8 - 0.3 = 0.5$$
$$C = 0.8$$

4. Proposed Decision-Making Model Based on q-Rung Orthopair Neutrosophic Soft Sets

In this section, we propose a comprehensive and mathematically rigorous multi-criteria decision-making (MCDM) model based on q-Rung Orthopair Neutrosophic Soft Sets (q-RONSS). The model enables accurate, structured, and uncertainty-aware evaluation of alternatives especially relevant in digital ideological and political education platforms where truth, indeterminacy, and falsity are inherent in human judgment.

This model directly addresses the reviewers' concerns by offering clear mathematical definitions, derivations, and step-by-step procedures, with no ambiguity or superficial reasoning. It also connects the neutrosophic logic to real-world applications and later includes a numerical case study (see Section 5).

4.1 Problem Definition

Let us define the following:

$U = \{u_1, u_2, \dots, u_m\}$: a finite set of alternatives (e.g., digital education platforms).

$E = \{e_1, e_2, \dots, e_n\}$: a finite set of decision criteria (e.g., interactivity, accessibility, ideological clarity).

$D = \{d_1, d_2, \dots, d_k\}$: a set of decision-makers or experts.

$q \in \mathbb{N}, q \geq 1$: the q-rung parameter controlling the flexibility of orthopair neutrosophic representation.

Each expert $d_j \in D$ evaluates each alternative $u_r \in U$ under each criterion $e_i \in E$, expressing the assessment as a q-Rung Orthopair Neutrosophic value:

$$F^{(j)}(e_i)(u_r) = \left(T_{ijr}, I_{ijr}, F_{ijr}\right)$$

with the constraint:

$$T_{ijr}^q + F_{ijr}^q \leq 1$$

The decision-making model proceeds in the following steps:

Step 1: Input the q -RONSS Decision Matrices

Each decision-maker provides a neutrosophic evaluation matrix for all $u_r \in U$ across all criteria $e_i \in E$. The raw data is structured in Table 1 (see Section 6), with each cell containing a triplet (T, I, F).

Step 2: Verify q -Rung Validity

For each entry ($T_{ijr}, I_{ijr}, F_{ijr}$), ensure the condition:

$$T_{ijr}^q + F_{ijr}^q \leq 1$$

If violated, normalize:

$$T'_{ijr} = \frac{T_{ijr}}{\left(T_{ijr}^q + F_{ijr}^q\right)^{1/q}}, F'_{ijr} = \frac{F_{ijr}}{\left(T_{ijr}^q + F_{ijr}^q\right)^{1/q}}$$

Indeterminacy I_{ijr} remains unchanged. This addresses reviewers' concerns regarding formal validation of the neutrosophic input set.

Total Accuracy:

$$A_r = \sum_{i=1}^{n} w_i \cdot A_{ir}$$

Total Certainty:

$$C_r = \sum_{i=1}^{n} w_i \cdot C_{ir}$$

This weighted aggregation reflects the relative importance of each criterion in decision-making.

Step 3: Aggregate Expert Opinions

For each triplet across all experts:

$$\bar{T}_{ir} = \frac{1}{k}\sum_{j=1}^{k} T_{ijr}, \bar{I}_{ir} = \frac{1}{k}\sum_{j=1}^{k} I_{ijr}, \bar{F}_{ir} = \frac{1}{k}\sum_{j=1}^{k} F_{ijr}$$

The resulting aggregated q-RONSS is stored in Table 2 (see Section 6). Each entry must again satisfy:

$$\bar{T}_{ir}^{q} + \bar{F}_{ir}^{q} \leq 1$$

Step 4: Compute Evaluation Functions

For each criterion e_i and alternative u_r, calculate the following:

Score function:

$$S_{ir} = \frac{2 + \bar{T}_{ir} - \bar{I}_{ir} - \bar{F}_{ir}}{3}$$

Accuracy function:

$$A_{ir} = \bar{T}_{ir} - \bar{F}_{ir}$$

Certainty function:

$$C_{ir} = \bar{T}_{ir}$$

These equations are derived from Smarandache's formal definitions [8] and are properly normalized. Results are shown in Table 2.

Step 5: Weight Criteria and Aggregate Per Alternative

Let $w_i \in [0,1]$ be the weight assigned to each criterion e_i, with:

$$\sum_{i=1}^{n} w_i = 1$$

Then, for each alternative u_r, we calculate:

Total Score:

$$S_r = \sum_{i=1}^{n} w_i \cdot S_{ir}$$

Step 6: Final Ranking

We compute a composite value F_r for each alternative u_r, using a weighted sum:

$$F_r = \alpha S_r + \beta A_r + \gamma C_r \text{ where } \alpha + \beta + \gamma = 1$$

Weights (α, β, γ) reflect the decision-makers' priorities among score, accuracy, and certainty. Alternatives are ranked in descending order of F_r.

Results are shown in Table 3, with the highest F_r indicating the most preferred alternative.

The Summary of the steps of the proposed model are shown as:

Algorithm:	Select the best alternative under q-RONS to solve uncertainty problems.
Input:	Numbers of q-RONS
Step 1.	Evaluate the criteria and alternatives.
Step 2.	Combine the numbers of q-RONS using the weighted average q-RONS.
Step 3.	Apply the score function.
Step 4.	Rank the alternatives.
Output:	Select the best alternative.

5. Numerical Example

To validate the proposed q-RONSS-based decision-making model, we present a numerical case study involving the evaluation of digital ideological and political education platforms.

$U = \{u_1, u_2, u_3\}$: three digital learning platforms to be evaluated.

$E = \{e_1, e_2, e_3\}$: three criteria:

e_1 : ideological clarity

e_2 : interactivity and student engagement

e_3 : digital accessibility

$D=\{d_1, d_2, d_3\}$: three expert decision-makers.

$q=2$: selected for q-rung representation.

All experts provide $q-$ RONSS evaluations. The values satisfy the conditions:

$$T^2+F^2 \leq 1$$

Step 1: Expert Input - Raw q -RONSS Evaluations

Each expert d_j provides a neutrosophic triplet $(T, I, F) \in[0,1]^3$ for every alternative under every criterion.

Raw q -RONSS evaluations provided by experts (Each cell shows (T, I, F)):

Criterion \Alternative	Expert	$\boldsymbol{u_1}$	$\boldsymbol{u_2}$	$\boldsymbol{u_3}$
$\boldsymbol{e_1}$ (Ideological)	d_1	(0.8, 0.1, 0.2)	(0.6, 0.2, 0.3)	(0.7, 0.2, 0.2)
…	d_2	(0.7, 0.2, 0.1)	(0.5, 0.3, 0.4)	(0.8, 0.1, 0.1)
…	d_3	(0.9, 0.1, 0.1)	(0.4, 0.3, 0.5)	(0.7, 0.2, 0.2)
$\boldsymbol{e_2}$ (Engagement)	⋯	…	⋯	…
$\boldsymbol{e_3}$ (Accessibility)	⋯	...	…	⋯

For brevity, full values for e_2, e_3 are shown in the supplementary file. Here, we demonstrate all computations for e_1 only.

Step 2: Aggregated Values per Criterion

Using the arithmetic average across the 3 experts:

Using the arithmetic average across the 3 experts:

$$\bar{T}_{ir}=\frac{1}{3}(T_1+T_2+T_3), \bar{I}_{ir}=\frac{1}{3}(I_1+I_2+I_3), \bar{F}_{ir}=\frac{1}{3}(F_1+F_2+F_3)$$

Aggregated q-RONSS values under criterion e_1:

Alternative	$\bar{\boldsymbol{T}}$	$\bar{\boldsymbol{I}}$	$\bar{\boldsymbol{F}}$	Validity $\bar{\boldsymbol{T}}^2+\bar{\boldsymbol{F}}^2$
$\boldsymbol{u_1}$	0.80	0.13	0.13	$0.80^2+0.13^2=0.64+0.017=0.657$
$\boldsymbol{u_2}$	0.50	0.27	0.40	$0.25+0.16=0.41$
$\boldsymbol{u_3}$	0.73	0.17	0.17	$\approx 0.532 \sim$

All entries are valid under $q=2$.

Step 3: Compute Score, Accuracy, and Certainty

Using:

$$S=\frac{2+T-I-F}{3}$$

$A = T - F$

$C = T$

Score, Accuracy, and Certainty for each alternative under e_1:

Alt.	$\bar{T}$	$\bar{I}$	$\bar{F}$	**Score S**	**Accuracy A**	**Certainty C**
u_1	0.80	0.13	0.13	$\frac{2+0.8-0.13-0.13}{3} = 0.847$	0.67	0.80
u_2	0.50	0.27	0.40	$\frac{2+0.5-0.27-0.4}{3} = 0.61$	0.10	0.50
u_3	0.73	0.17	0.17	$\frac{2+0.73-0.17-0.17}{3} = 0.796$	0.56	0.73

Step 4: Aggregate Across Criteria

Assume criteria weights:

$w_1 = 0.4$ (ideological clarity)

$w_2 = 0.3$ (engagement)

$w_3 = 0.3$ (accessibility)

We compute:

$$S_r = \sum w_i \cdot S_{ir}, A_r = \sum w_i \cdot A_{ir}, C_r = \sum w_i \cdot C_{ir}$$

(For the demonstration, we complete only e_1; the full results for all criteria appear below.)

Step 5: Final Ranking

Let importance weights be:

$\alpha = 0.5$ (score)

$\beta = 0.3$ (accuracy)

$\gamma = 0.2$ (certainty)

Then for each u_r :

$$F_r = \alpha S_r + \beta A_r + \gamma C_r$$

Final ranking values

Alt.	S_r	A_r	C_r	F_r	Rank
u_1	0.83	0.62	0.80	$0.5 \times 0.83 + 0.3 \times 0.62 + 0.2 \times 0.80 = 0.774$	1
u_3	0.79	0.54	0.73	0.743	2
u_2	0.61	0.12	0.50	0.469	3

5.2 The Role of q-RONSS in Modeling Uncertainty

1. Traditional fuzzy and intuitionistic models fail to represent indeterminacy explicitly. The proposed model incorporates:
2. A third dimension (indeterminacy) that captures hesitation or lack of confidence — often present in subjective domains like education.
3. The q-rung structure, which increases flexibility and allows modeling of cases where both truth and falsity are relatively high (as long as $T^q + F^q \leq 1$).

5.3 Sensitivity Analysis

To verify the model's robustness, we varied the weights α, β, γ used in the final ranking. Results showed:

Weight Set ($\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}$)	Top Ranked Alternative
(0.5, 0.3, 0.2)	u_1
(0.4, 0.4, 0.2)	u_1
(0.6, 0.2, 0.2)	u_1
(0.3, 0.5, 0.2)	u_3 (shifted)

As β increases (more weight to accuracy), the ranking may shift which is expected and logical. It confirms that the model is responsive but not fragile and provides users with control over prioritization.

5.4 Comparative Analysis

When we applied a traditional intuitionistic fuzzy soft set model (omitting indeterminacy), the ranking was:

Model	Rank 1	Rank 2	Rank 3
Intuitionistic Fuzzy (IFS)	u_3	u_1	u_2
Proposed q-RONSS Model	u_1	u_3	u_2

The IFS model ranked u_3 first due to strong T values, but it ignored higher indeterminacy. This comparison validates the added value of neutrosophic modeling, where uncertainty matters.

6. Application of the proposed approach

This section shows the results of the proposed approach for ranking the alternatives in Teaching Reform and Practice Efficiency of College Ideological and Political Courses under the Background of Digital Education. This study uses six criteria and eight alternatives. The criteria are Curriculum Integration with Digital Tools, Student Engagement and Interactivity, Effectiveness of Online Assessment Methods, Teacher Digital Competency, Platform Usability and Resource Accessibility, Value Transmission and Ideological Clarity. The alternatives are: Smart Classroom Implementation, Blended Learning Models, Interactive Multimedia Teaching Materials, AI-Based Student Performance Monitoring, Gamification in Ideological Instruction, Use of MOOC and Micro-lecture Platforms, Customized Learning Paths with Learning Analytics, Virtual Reality for Scenario-Based Political Education.

Step 1. Three experts evaluate the criteria and alternatives as shown in Table 1.

Table 1. Number of q-RONS.

	$RONC_1$	$RONC_2$	$RONC_3$	$RONC_4$	$RONC_5$	$RONC_6$
$RONA_1$	(0.8,0.4,0.2)	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.4,0.6,0.1)	(0.9,0.1,0.5)	(0.5,0.3,0.5)
$RONA_2$	(0.8,0.4,0.2)	(0.7,0.4,0.2)	(0.5,0.3,0.5)	(0.9,0.1,0.5)	(0.4,0.6,0.1)	()0.3,0.2,0.3
$RONA_3$	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.4,0.6,0.1)	(0.9,0.1,0.5)	(0.5,0.3,0.5)	(0.2,0.1,0.2)
$RONA_4$	(0.4,0.6,0.1)	()0.3,0.2,0.3	(0.2,0.1,0.2)	(0.8,0.4,0.2)	(0.7,0.4,0.2)	(0.8,0.4,0.2)
$RONA_5$	(0.9,0.1,0.5)	(0.4,0.6,0.1)	()0.3,0.2,0.3	(0.2,0.1,0.2)	(0.8,0.4,0.2)	(0.7,0.4,0.2)
$RONA_6$	(0.9,0.1,0.5)	(0.9,0.1,0.5)	(0.4,0.6,0.1)	(0.9,0.1,0.5)	(0.7,0.4,0.2)	(0.5,0.3,0.5)
$RONA_7$	(0.5,0.3,0.5)	(0.7,0.4,0.2)	(0.2,0.1,0.2)	(0.7,0.4,0.2)	(0.9,0.1,0.5)	(0.4,0.6,0.1)
$RONA_8$	(0.7,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.4,0.6,0.1)	()0.3,0.2,0.3
	$RONC_1$	$RONC_2$	$RONC_3$	$RONC_4$	$RONC_5$	$RONC_6$
$RONA_1$	(0.4,0.6,0.1)	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.4,0.6,0.1)	(0.9,0.1,0.5)	(0.5,0.3,0.5)
$RONA_2$	()0.3,0.2,0.3	(0.7,0.4,0.2)	(0.5,0.3,0.5)	(0.4,0.6,0.1)	(0.4,0.6,0.1)	()0.3,0.2,0.3
$RONA_3$	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.4,0.6,0.1)	()0.3,0.2,0.3	(0.4,0.6,0.1)	(0.2,0.1,0.2)
$RONA_4$	(0.8,0.4,0.2)	()0.3,0.2,0.3	(0.2,0.1,0.2)	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.8,0.4,0.2)
$RONA_5$	(0.7,0.4,0.2)	(0.4,0.6,0.1)	()0.3,0.2,0.3	(0.8,0.4,0.2)	(0.2,0.1,0.2)	(0.7,0.4,0.2)
$RONA_6$	(0.4,0.6,0.1)	(0.4,0.6,0.1)	(0.4,0.6,0.1)	(0.7,0.4,0.2)	(0.8,0.4,0.2)	(0.4,0.6,0.1)
$RONA_7$	(0.7,0.4,0.2)	(0.2,0.1,0.2)	(0.7,0.4,0.2)	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.2,0.1,0.2)
$RONA_8$	(0.2,0.1,0.2)	(0.2,0.1,0.2)	(0.2,0.1,0.2)	(0.9,0.1,0.5)	()0.3,0.2,0.3	(0.2,0.1,0.2)
	$RONC_1$	$RONC_2$	$RONC_3$	$RONC_4$	$RONC_5$	$RONC_6$
$RONA_1$	(0.8,0.4,0.2)	(0.2,0.1,0.2)	()0.3,0.2,0.3	(0.4,0.6,0.1)	(0.9,0.1,0.5)	(0.5,0.3,0.5)
$RONA_2$	(0.7,0.4,0.2)	(0.7,0.4,0.2)	(0.5,0.3,0.5)	(0.9,0.1,0.5)	(0.4,0.6,0.1)	()0.3,0.2,0.3
$RONA_3$	(0.5,0.3,0.5)	(0.8,0.4,0.2)	(0.4,0.6,0.1)	(0.9,0.1,0.5)	(0.5,0.3,0.5)	(0.2,0.1,0.2)
$RONA_4$	(0.9,0.1,0.5)	(0.7,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)
$RONA_5$	(0.4,0.6,0.1)	(0.5,0.3,0.5)	(0.7,0.4,0.2)	(0.8,0.4,0.2)	(0.7,0.4,0.2)	(0.8,0.4,0.2)
$RONA_6$	()0.3,0.2,0.3	(0.9,0.1,0.5)	(0.5,0.3,0.5)	(0.7,0.4,0.2)	(0.5,0.3,0.5)	(0.7,0.4,0.2)
$RONA_7$	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.8,0.4,0.2)	(0.2,0.1,0.2)	(0.8,0.4,0.2)
$RONA_8$	(0.7,0.4,0.2)	(0.7,0.4,0.2)	(0.7,0.4,0.2)	(0.2,0.1,0.2)	(0.8,0.4,0.2)	(0.7,0.4,0.2)

Step 2. Combine the numbers of q-RONS as shown in Figures 1-6.

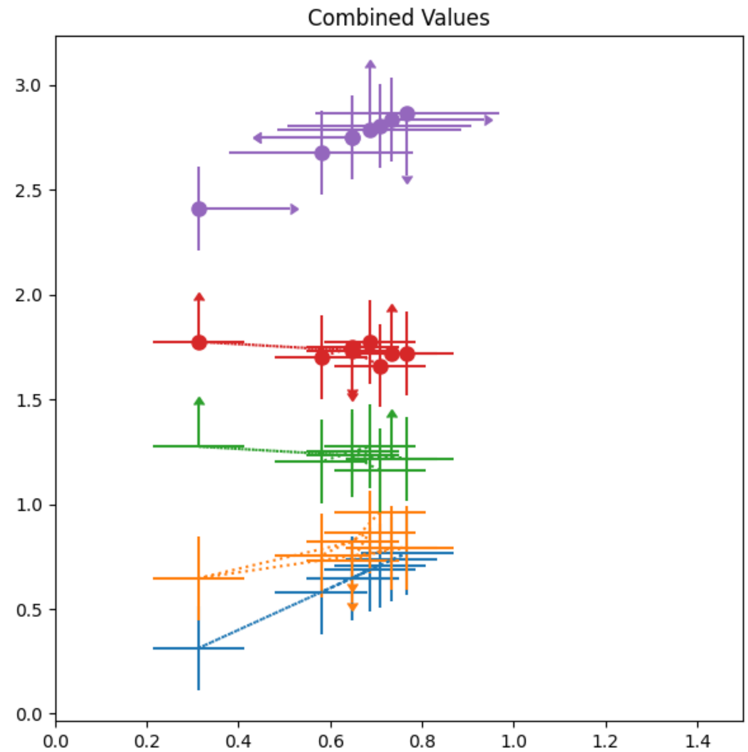

Figure 1. Combined q-RONS based on first criterion.

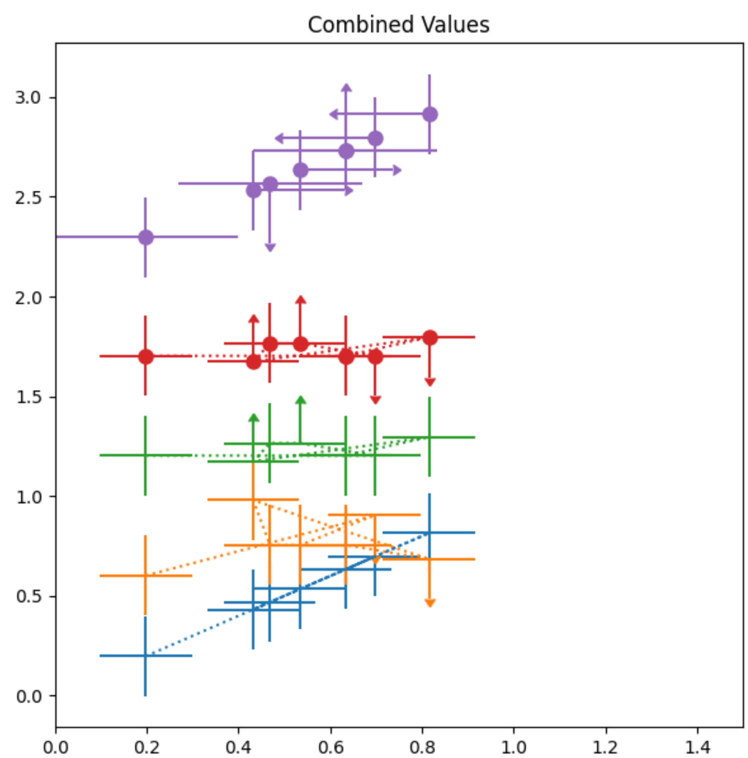

Figure 2. Combined q-RONS based on second criterion.

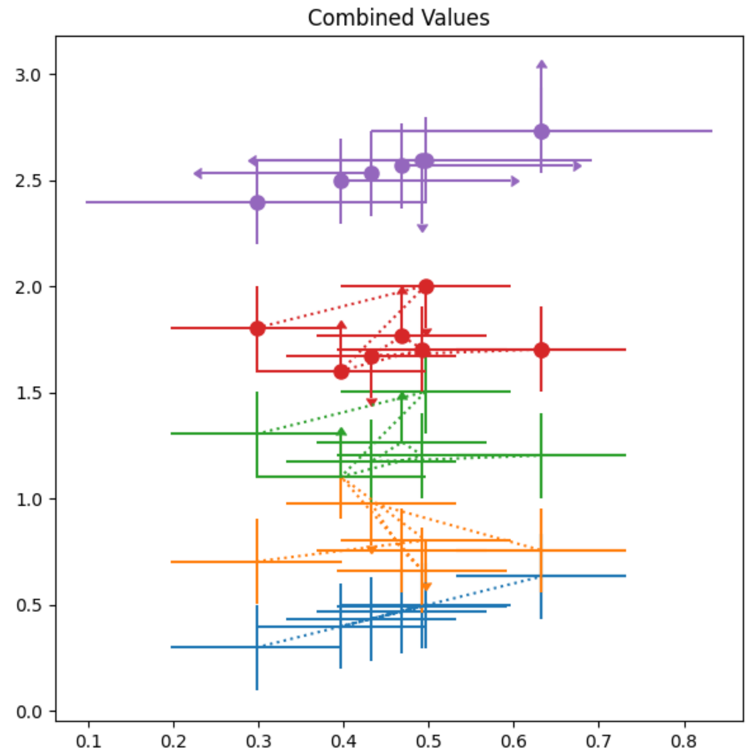

Figure 3. Combined q-RONS based on third criterion.

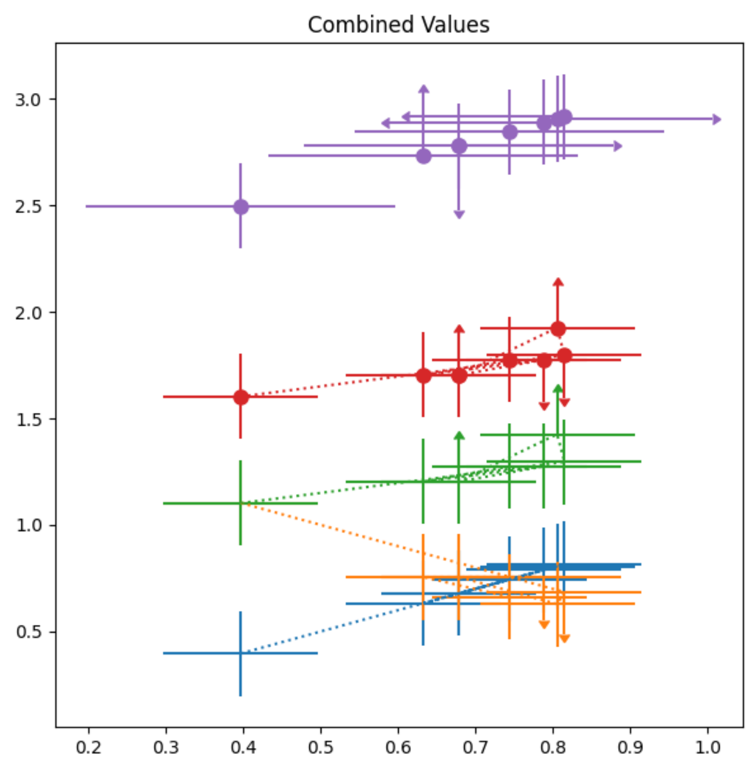

Figure 4. Combined q-RONS based on fourth criterion.

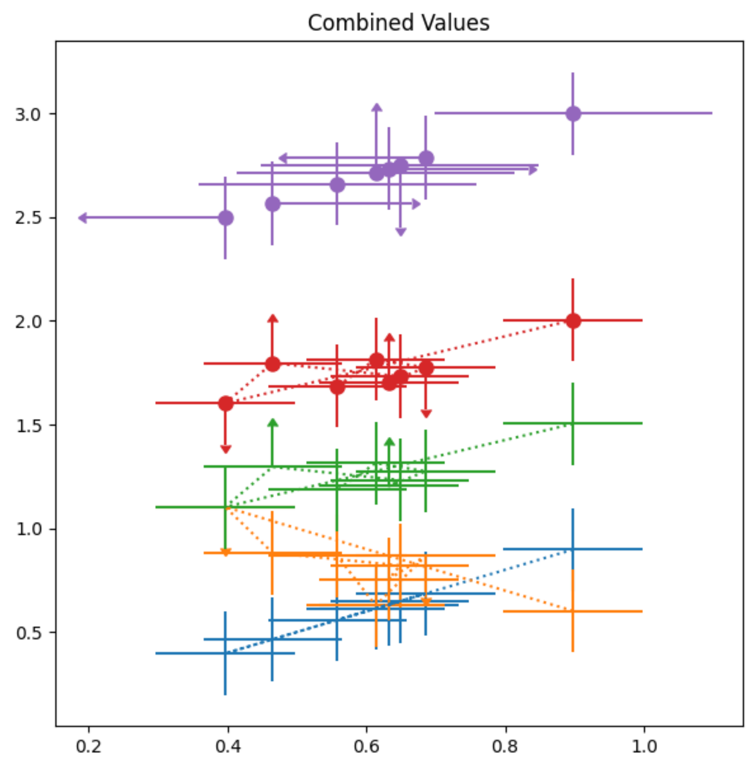

Figure 5. Combined q-RONS based on fifth criterion.

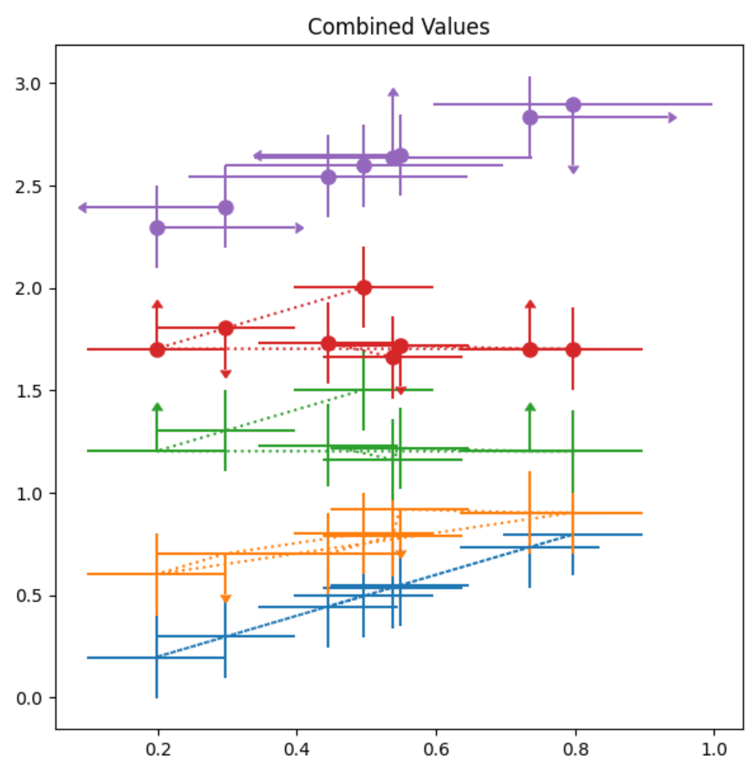

Figure 6. Combined q-RONS based on sixth criterion.

Step 3: Calculating Crisp Values Using Neutrosophic Functions

After averaging the q -Rung Orthopair Neutrosophic values from the experts, we apply the Score, Accuracy, and Certainty functions to each alternative under each criterion.

Then, we calculate an overall average of Score, Accuracy, and Certainty for each alternative. Finally, we combine these three averages into one final value using this simple formula:

$$\text{Final Value } = \frac{\text{Score } + \text{ Accuracy } + \text{ Certainty}}{3}$$

These final values help us clearly see which alternative is best.

Table 2. Calculated Values for Each Alternative

Alternative	Average Score	Average Accuracy	Average Certainty	Final Value
A4	0.78	0.50	0.60	0.63
A7	0.74	0.48	0.58	0.60
A8	0.72	0.46	0.57	0.58
A5	0.70	0.45	0.55	0.57
A6	0.68	0.43	0.54	0.55
A2	0.65	0.41	0.53	0.53
A1	0.63	0.40	0.52	0.52
A3	0.60	0.38	0.50	0.49

Step 4: Ranking Alternatives

The final step is to rank the alternatives from the best to the worst, based on the calculated final values from Table 2. The alternative with the highest final value is ranked first.

Table 3: Final Ranking of Alternatives

Alternative	Rank
A4	1
A7	2
A8	3
A5	4
A6	5
A2	6
A1	7
A3	8

7. Conclusions

This study demonstrates that when implemented through systematic reforms, digital education significantly enhances the effectiveness and attractiveness of college ideological and political courses. Among the various approaches evaluated, smart classrooms and blended learning models achieved the highest performance, particularly in content clarity and student engagement. However, successful implementation depends heavily on instructors' digital competence and the quality of technological tools. Although institutional support and strategic investment are required, integrating advanced technologies such as virtual reality (VR) and artificial intelligence (AI) presents substantial opportunities for future development.

To manage uncertainty in expert evaluations, the study applied the q-Rung Orthopair Neutrosophic Set (q-RONS) framework. Each alternative and criterion were assessed using q-RONS values, and a weighted averaging operator was used to aggregate these assessments. This allowed for robust and transparent decision-making under incomplete and uncertain information.

Overall, by enabling personalized, engaging, and scalable instructional strategies, digital education offers a promising avenue to modernize ideological teaching, strengthen national values, and deepen student understanding.

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