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# SuperHyperSoft Set with MCDM Methods for Assessment of Ideological and Political Education in Colleges and Universities Under the Background of Big Data

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**Abstract**: The integration of big data into ideological and political education (IPE) in colleges and universities has reshaped traditional teaching methodologies, offering new ways to analyze student behavior, personalizing learning experiences, and enhance educational outcomes. As digital transformation accelerates, the need for an effective evaluation system to assess the impact of big data-driven IPE becomes essential. This paper uses the multicriteria decision making (MCDM) methodology for evaluating this problem. Two MCDM methods are used such as CRITIC methodology to compute the criteria weights and the MABAC methodology to rank the alternatives. We use the SuperHyperSoft set to deal with criteria and sub criteria. This study uses eight criteria and seven alternatives. We introduce the ranking of alternatives into four HyperSoft sets and in each set, we obtain the rank of alternatives.

**Keywords**: SuperHyperSoft Set; Ideological and Political Education; Big Data; Ideological and Political Education.

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## 1. Introduction

In the digital age, the role of big data in higher education has become increasingly significant, revolutionizing the way knowledge is delivered and assessed. Among the various fields impacted, ideological and political education (IPE) has witnessed substantial transformation, shifting from conventional lecture-based instruction to data-driven, interactive, and adaptive learning models. Colleges and universities are now leveraging artificial intelligence, cloud computing, and real-time analytics to tailor educational content, monitor student engagement, and predict learning outcomes. However, despite these advancements, there remains a pressing need to establish an effective evaluation system that can measure the success of these new teaching methodologies and ensure that IPE continues to fulfill its mission of fostering critical thinking, civic responsibility, and ethical leadership among students[1], [2]. Evaluating the effectiveness of IPE under the background of big data requires a multi-dimensional approach.

Traditional evaluation methods, such as student surveys and academic assessments, no longer suffice in capturing the complexity of modern educational environments. Instead, a comprehensive framework that integrates quantitative and qualitative factors—such as curriculum relevance, teaching quality, student engagement, technological integration, and big data application—is necessary to provide a holistic view of IPE's impact[3], [4]. Through big data analytics, educators can track learning behaviors, measure knowledge retention, and refine teaching methods based on real-time feedback, thereby enhancing the precision and effectiveness of IPE delivery.

Despite its potential, the implementation of big data-driven IPE evaluation is not without challenges. Ethical concerns regarding student data privacy, digital literacy gaps among faculty, and the risk of excessive reliance on automated assessments pose significant obstacles. Additionally, the effectiveness of big data applications depends on the quality of the data collected, the analytical models used, and the extent to which educators and administrators are trained to interpret and utilize these insights[5], [6]. Therefore, a systematic and structured approach to evaluating IPE effectiveness must address both the technological advantages and the practical limitations associated with big data integration in education.

To bridge this gap, this study proposes an evaluation framework based on Multi-Criteria Decision-Making (MCDM) methodologies to systematically rank and assess various big data-driven IPE strategies. By applying these methods, institutions can identify the most effective educational approaches, optimize resource allocation, and refine their curricula to meet the evolving needs of students. Moreover, the results of this research can serve as a guide reference for educational policymakers, university administrators, and instructors in enhancing IPE quality through data-driven insights[7], [8].

Ultimately, as digital transformation continues to shape higher education, the need for a robust and adaptable evaluation mechanism becomes more crucial than ever. By integrating big data analytics with structured evaluation frameworks, universities can ensure that ideological and political education remains relevant, impactful, and aligned with the broader educational objectives of nurturing informed, responsible, and engaged citizens. This study aims to contribute to the ongoing discourse on IPE modernization by offering a strategic roadmap for optimizing its effectiveness in the era of big data[9], [10].

## 2. SuperHyperSoft-CRITIC-MABAC

We introduce the concept of SuperHyperSoft set with two MCDM methods such as CRITIC method to compute the criteria weights and ranking the alternatives.

SuperHyperSoft Set

Smarandache presents the SuperHyperSoft set which is an extension of HyperSoft set and has different HyperSoft sets. We use the SuperHyperSoft set to deal with different criteria values in the ranking the alternatives[11], [12].

Let U a universe discourse and K is a non-empty set; we can define the power set as P(K). let we have different criteria such as $E_1, E_2, E_3$ and their powerset can be defined as $P(E_1), P(E_2), P(E_3)$ [13], [14]

We can define the SuperHyperSoft set as:

$$F: P(E_1) \times P(E_2) \times P(E_3) \rightarrow P(K) \quad (1)$$

CRITIC Method

We use the CRITIC method in this study to compute the criteria weights[15], [16].

Create the decision matrix.

$$Y = \begin{pmatrix} y_{11} & \cdots & y_{1n} \\ \vdots & \ddots & \vdots \\ y_{m1} & \cdots & y_{mn} \end{pmatrix}_{m \times n} ; i = 1, \dots, m; j = 1, \dots, n \quad (2)$$

Normalize the decision matrix.

The decision matrix is normalized based on beneficial criteria and non-beneficial criteria such as:

$$x_{ij} = \frac{y_{ij} - y_i^-}{y_i^+ - y_i^-} \quad (3)$$

$$x_{ij} = \frac{y_{ij} - y_i^+}{y_i^- - y_i^+} \quad (4)$$

$$\begin{pmatrix} y_i^+ = \max(y_1, \dots . y_m) \\ y_i^- = \min(y_1, \dots . y_m) \end{pmatrix} \quad (5)$$

Determine the correlation between the criteria $\beta_{jk}$ .

Compute the standard deviation for each criterion $\aleph_j$

Compute the C index

$$C_j = \aleph_j \sum_{k=1}^{n} (1 - \beta_{jk}) \quad (6)$$

Compute the criteria weights.

$$w_j = \frac{C_j}{\sum_{j=1}^{n} C_j} \quad (7)$$

MABAC Method

This study uses the MABAC method to rank the alternatives[17], [18].

Normalize the decision matrix

$$u_{ij} = \frac{y_{ij} - y_i^-}{y_i^+ - y_i^-} \quad (8)$$

$$u_{ij}=\frac{y_{ij}-y_i^+}{y_i^- -y_i^+} \tag{9}$$

Compute the weighted normalized decision matrix.

$$r_{ij}=w_j+w_j u_{ij} \tag{10}$$

Compute the border approximation area matrix.

$$t_j=\left(\prod_{i=1}^{m} r_{ij}\right)^{\frac{1}{m}} \tag{11}$$

Compute the distance from the $t_j$ values.

$$d_j=r_{ij}-t_j \tag{12}$$

Compute the total distance

$$S_i=\sum_{j=1}^{n} d_{ij} \tag{13}$$

**3. Case Study**

This section shows the case study of this paper by implementing the proposed approach. This study uses eight criteria and seven alternatives such as: Curriculum Relevance(Highly Relevant, Weakly Relevant), Technology Integration (Advanced, Basic), Practical Impact on Students (Significant, Moderate, Insignificant), Student Engagement (High, Medium, Low), Big Data Application (Extensive, Adequate, Minimal), Evaluation and Feedback Mechanisms (Comprehensive, Standard, Limited), Teaching Quality (Excellent, Good, Average, Poor), Faculty Competency (Highly Competent, Competent, Needs Improvement). In each criterion, there are different values to present it.

We create the decision matrix using Eq. (2) between the criteria and alternatives. Three experts are invited to evaluate the criteria and alternatives. They used scale between 0.1 to 0.9.

We normalize the decision matrix using Eq. (3) as shown in Table 1.

We determine the correlation between the criteria $\beta_{jk}$.

We compute the standard deviation for each criterion $\aleph_j$

We compute the C index using Eq. (6).

We compute the criteria weights using Eq. (7) as shown in Table 2.

Table 1. Normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | -0.04375 | -1 | -0.39083 | -1 | -0.64242 | -0.1369 | 0 | -0.461 |
| $A_2$ | 0 | 0 | 0 | -0.65524 | -1 | -0.34395 | -0.07253 | -1 |
| $A_3$ | -1 | -0.07018 | -0.84779 | -0.41379 | -0.38054 | -1 | -1 | -0.61517 |

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| $A_4$ | -0.29852 | -0.139 | -1 | -0.24391 | -0.14279 | 0 | -0.96583 | 0 |
| $A_5$ | -0.40403 | -0.31994 | -0.28209 | -0.24391 | -0.59522 | -0.11408 | -0.48502 | -0.25586 |
| $A_6$ | -0.51059 | -0.36155 | -0.56519 | 0 | 0 | -0.29802 | -0.65586 | 0 |
| $A_7$ | -0.59549 | -0.22259 | -0.4344 | 0.343832 | -0.57108 | -0.29801 | -0.10419 | -0.61517 |

Table 2. Criteria weights.

| Criteria | Weights |
|---|---|
| $C_1$ | 0.11176 |
| $C_2$ | 0.1319272 |
| $C_3$ | 0.12239 |
| $C_4$ | 0.143527 |
| $C_5$ | 0.122404 |
| $C_6$ | 0.091427 |
| $C_7$ | 0.158943 |
| $C_8$ | 0.117621 |

We use the SuperHyperSoft set to divide the set of criteria values into different HyperSoft set such as: (Highly Relevant, Weakly Relevant), (Advanced, Basic), (Significant), (High), (Extensive), (Comprehensive), (Excellent), (Highly Competent).

First HyperSoft Set:

(Highly Relevant), (Advanced), (Significant), (High), (Extensive), (Comprehensive), (Excellent), (Highly Competent)

Second HyperSoft Set:

(Highly Relevant), (Basic), (Significant), (High), (Extensive), (Comprehensive), (Excellent), (Highly Competent)

Third HyperSoft Set:

(Weakly Relevant), Advanced), (Significant), (High), (Extensive), (Comprehensive), (Excellent), (Highly Competent)

Fourth HyperSoft Set:

(Weakly Relevant), (Basic), (Significant), (High), (Extensive), (Comprehensive), (Excellent), (Highly Competent)

Then we apply MABAC in each HyperSoft set.

First HyperSoft Set.

Eq. (8) is used to normalize the decision matrix as shown in Table 3.

Eq. (10) is used to compute the weighted normalized decision matrix as shown in Table 4.

Eq. (11) is used to compute the border approximation area matrix.

Eq. (12) is used to compute the distance from the $t_j$ values as shown in Table 5.

Eq. (13) is used to compute the total distance.

Table 3. Normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.04375 | 1 | 0.390828 | 1 | 0.64242 | 0.136901 | 0 | 0.460998 |
| $A_2$ | 0 | 0 | 0 | 0.743448 | 1 | 0.343948 | 0.072528 | 1 |
| $A_3$ | 1 | 0.070183 | 0.847788 | 0.56378 | 0.380539 | 1 | 1 | 0.615171 |
| $A_4$ | 0.29852 | 0.139002 | 1 | 0.437363 | 0.142785 | 0 | 0.965833 | 0 |
| $A_5$ | 0.404034 | 0.319945 | 0.282087 | 0.437363 | 0.595215 | 0.114084 | 0.485021 | 0.25586 |
| $A_6$ | 0.510595 | 0.361549 | 0.565192 | 0.25586 | 0 | 0.298019 | 0.655857 | 0 |
| $A_7$ | 0.595486 | 0.222591 | 0.434397 | 0 | 0.571076 | 0.298014 | 0.104195 | 0.615171 |

Table 4. Weighted normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.11665 | 0.263854 | 0.170223 | 0.287054 | 0.201039 | 0.103944 | 0.158943 | 0.171844 |
| $A_2$ | 0.11176 | 0.131927 | 0.12239 | 0.250232 | 0.244808 | 0.122874 | 0.170471 | 0.235242 |
| $A_3$ | 0.223521 | 0.141186 | 0.226151 | 0.224444 | 0.168983 | 0.182855 | 0.317887 | 0.189978 |
| $A_4$ | 0.145123 | 0.150265 | 0.24478 | 0.2063 | 0.139881 | 0.091427 | 0.312456 | 0.117621 |
| $A_5$ | 0.156915 | 0.174137 | 0.156915 | 0.2063 | 0.19526 | 0.101858 | 0.236034 | 0.147715 |
| $A_6$ | 0.168825 | 0.179625 | 0.191564 | 0.18025 | 0.122404 | 0.118675 | 0.263187 | 0.117621 |
| $A_7$ | 0.178312 | 0.161293 | 0.175556 | 0.143527 | 0.192306 | 0.118674 | 0.175504 | 0.189978 |

Table 5. Distance values.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | -0.03674 | 0.096182 | -0.00962 | 0.077489 | 0.024487 | -0.0134 | -0.06622 | 0.009425 |
| $A_2$ | -0.04163 | -0.03574 | -0.05746 | 0.040667 | 0.068256 | 0.005533 | -0.05469 | 0.072823 |
| $A_3$ | 0.070134 | -0.02649 | 0.046303 | 0.01488 | -0.00757 | 0.065514 | 0.092723 | 0.027559 |
| $A_4$ | -0.00826 | -0.01741 | 0.064932 | -0.00326 | -0.03667 | -0.02591 | 0.087293 | -0.0448 |
| $A_5$ | 0.003529 | 0.006465 | -0.02293 | -0.00326 | 0.018708 | -0.01548 | 0.010871 | -0.0147 |
| $A_6$ | 0.015438 | 0.011953 | 0.011716 | -0.02931 | -0.05415 | 0.001334 | 0.038024 | -0.0448 |
| $A_7$ | 0.024926 | -0.00638 | -0.00429 | -0.06604 | 0.015754 | 0.001333 | -0.04966 | 0.027559 |

Second HyperSoft Set.

Eq. (8) is used to normalize the decision matrix as shown in Table 6.

Eq. (10) is used to compute the weighted normalized decision matrix as shown in Table 7.

Eq. (11) is used to compute the border approximation area matrix.

Eq. (12) is used to compute the distance from the $t_j$ values as shown in Table 8.

Eq. (13) is used to compute the total distance.

Table 6. Normalized decision matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| A1 | 0.04375 | 1 | 0.390828 | 1 | 0.64242 | 0.136901 | 0 | 0.460998 |
| A2 | 0 | 0.239888 | 0 | 0.743448 | 1 | 0.343948 | 0.072528 | 1 |
| A3 | 1 | 0 | 0.847788 | 0.56378 | 0.380539 | 1 | 1 | 0.615171 |
| A4 | 0.29852 | 0.520368 | 1 | 0.437363 | 0.142785 | 0 | 0.965833 | 0 |
| A5 | 0.404034 | 0.746629 | 0.282087 | 0.437363 | 0.595215 | 0.114084 | 0.485021 | 0.25586 |
| A6 | 0.510595 | 0.280161 | 0.565192 | 0.25586 | 0 | 0.298019 | 0.655857 | 0 |
| A7 | 0.595486 | 0.426875 | 0.434397 | 0 | 0.571076 | 0.298014 | 0.104195 | 0.615171 |

Table 7. Weighted normalized decision matrix.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| A1 | 0.117518 | 0.282506 | 0.164584 | 0.288811 | 0.198659 | 0.107814 | 0.146301 | 0.177258 |
| A2 | 0.112592 | 0.175138 | 0.118336 | 0.251763 | 0.24191 | 0.127448 | 0.156912 | 0.242653 |
| A3 | 0.225184 | 0.141253 | 0.218659 | 0.225819 | 0.166983 | 0.189663 | 0.292602 | 0.195963 |
| A4 | 0.146203 | 0.214757 | 0.236671 | 0.207563 | 0.138225 | 0.094831 | 0.287604 | 0.121326 |
| A5 | 0.158083 | 0.246717 | 0.151717 | 0.207563 | 0.192949 | 0.10565 | 0.21726 | 0.152369 |
| A6 | 0.170081 | 0.180827 | 0.185218 | 0.181353 | 0.120955 | 0.123093 | 0.242254 | 0.121326 |
| A7 | 0.179639 | 0.201551 | 0.16974 | 0.144406 | 0.190029 | 0.123092 | 0.161545 | 0.195963 |

Table 8. Distance values.

| | C1 | C2 | C3 | C4 | C5 | C6 | C7 | C8 |
|---|---|---|---|---|---|---|---|---|
| A1 | -0.03701 | 0.080988 | -0.00931 | 0.077964 | 0.024197 | -0.0139 | -0.06095 | 0.009722 |
| A2 | -0.04194 | -0.02638 | -0.05555 | 0.040916 | 0.067448 | 0.005739 | -0.05034 | 0.075118 |
| A3 | 0.070656 | -0.06027 | 0.044769 | 0.014971 | -0.00748 | 0.067953 | 0.085348 | 0.028428 |
| A4 | -0.00832 | 0.013239 | 0.062781 | -0.00328 | -0.03624 | -0.02688 | 0.08035 | -0.04621 |
| A5 | 0.003555 | 0.045199 | -0.02217 | -0.00328 | 0.018487 | -0.01606 | 0.010006 | -0.01517 |
| A6 | 0.015553 | -0.02069 | 0.011328 | -0.02949 | -0.05351 | 0.001383 | 0.035 | -0.04621 |
| A7 | 0.025111 | 3.24E-05 | -0.00415 | -0.06644 | 0.015567 | 0.001383 | -0.04571 | 0.028428 |

Third HyperSoft Set.

Eq. (8) is used to normalize the decision matrix as shown in Table 9.

Eq. (10) is used to compute the weighted normalized decision matrix as shown in Table 10.

Eq. (11) is used to compute the border approximation area matrix.

Eq. (12) is used to compute the distance from the $t_j$ values as shown in Table 11.

Eq. (13) is used to compute the total distance.

Table 9. Normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.210384 | 1 | 0.390828 | 1 | 0.64242 | 0.136901 | 0 | 0.460998 |
| $A_2$ | 0.105192 | 0 | 0 | 0.743448 | 1 | 0.343948 | 0.072528 | 1 |
| $A_3$ | 0 | 0.070183 | 0.847788 | 0.56378 | 0.380539 | 1 | 1 | 0.615171 |
| $A_4$ | 0.351175 | 0.139002 | 1 | 0.437363 | 0.142785 | 0 | 0.965833 | 0 |
| $A_5$ | 1 | 0.319945 | 0.282087 | 0.437363 | 0.595215 | 0.114084 | 0.485021 | 0.25586 |
| $A_6$ | 0.666688 | 0.361549 | 0.565192 | 0.25586 | 0 | 0.298019 | 0.655857 | 0 |
| $A_7$ | 0.438504 | 0.222591 | 0.434397 | 0 | 0.571076 | 0.298014 | 0.104195 | 0.615171 |

Table 10. Weighted normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.169237 | 0.231134 | 0.169447 | 0.267068 | 0.187566 | 0.11723 | 0.149977 | 0.178176 |
| $A_2$ | 0.154529 | 0.115567 | 0.121832 | 0.232809 | 0.228402 | 0.138579 | 0.160854 | 0.24391 |
| $A_3$ | 0.139821 | 0.123678 | 0.225119 | 0.208818 | 0.157659 | 0.206227 | 0.299953 | 0.196978 |
| $A_4$ | 0.188923 | 0.131631 | 0.243663 | 0.191937 | 0.130507 | 0.103114 | 0.294829 | 0.121955 |
| $A_5$ | 0.279642 | 0.152542 | 0.156199 | 0.191937 | 0.182175 | 0.114877 | 0.222718 | 0.153158 |
| $A_6$ | 0.233038 | 0.15735 | 0.19069 | 0.1677 | 0.114201 | 0.133843 | 0.24834 | 0.121955 |
| $A_7$ | 0.201133 | 0.141291 | 0.174755 | 0.133534 | 0.179419 | 0.133843 | 0.165603 | 0.196978 |

Table 11. Distance values.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | -0.02111 | 0.084255 | -0.00958 | 0.072094 | 0.022846 | -0.01511 | -0.06248 | 0.009773 |
| $A_2$ | -0.03582 | -0.03131 | -0.0572 | 0.037836 | 0.063682 | 0.00624 | -0.05161 | 0.075507 |
| $A_3$ | -0.05053 | -0.0232 | 0.046092 | 0.013844 | -0.00706 | 0.073888 | 0.087493 | 0.028575 |
| $A_4$ | -0.00143 | -0.01525 | 0.064636 | -0.00304 | -0.03421 | -0.02923 | 0.082368 | -0.04645 |
| $A_5$ | 0.089292 | 0.005663 | -0.02283 | -0.00304 | 0.017455 | -0.01746 | 0.010258 | -0.01524 |
| $A_6$ | 0.042688 | 0.010471 | 0.011663 | -0.02727 | -0.05052 | 0.001504 | 0.035879 | -0.04645 |
| $A_7$ | 0.010783 | -0.00559 | -0.00427 | -0.06144 | 0.014698 | 0.001503 | -0.04686 | 0.028575 |

Fourth HyperSoft Set.

Eq. (8) is used to normalize the decision matrix as shown in Table 12.

Eq. (10) is used to compute the weighted normalized decision matrix as shown in Table 13.

Eq. (11) is used to compute the border approximation area matrix.

Eq. (12) is used to compute the distance from the $t_j$ values as shown in Table 14.

Eq. (13) is used to compute the total distance.

Table 12. Normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.363133 | 0.294418 | 0.390828 | 1 | 0.64242 | 0.136901 | 0 | 0.460998 |
| $A_2$ | 1 | 0.404824 | 0 | 0.743448 | 1 | 0.343948 | 0.072528 | 1 |
| $A_3$ | 0.423855 | 0 | 0.847788 | 0.56378 | 0.380539 | 1 | 1 | 0.615171 |
| $A_4$ | 0.787711 | 0.33122 | 1 | 0.437363 | 0.142785 | 0 | 0.965833 | 0 |
| $A_5$ | 0.696866 | 0.220813 | 0.282087 | 0.437363 | 0.595215 | 0.114084 | 0.485021 | 0.25586 |
| $A_6$ | 0.060722 | 0.297094 | 0.565192 | 0.25586 | 0 | 0.298019 | 0.655857 | 0 |
| $A_7$ | 0 | 1 | 0.434397 | 0 | 0.571076 | 0.298014 | 0.104195 | 0.615171 |

Table 13. Weighted normalized decision matrix.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | 0.141784 | 0.346854 | 0.153904 | 0.238062 | 0.145678 | 0.098066 | 0.133978 | 0.130621 |
| $A_2$ | 0.208026 | 0.376439 | 0.110656 | 0.207524 | 0.177394 | 0.115926 | 0.143695 | 0.178811 |
| $A_3$ | 0.1481 | 0.267962 | 0.204469 | 0.186138 | 0.12245 | 0.172515 | 0.267956 | 0.144405 |
| $A_4$ | 0.185946 | 0.356716 | 0.221313 | 0.17109 | 0.101362 | 0.086258 | 0.263379 | 0.089405 |
| $A_5$ | 0.176496 | 0.327131 | 0.141871 | 0.17109 | 0.141491 | 0.096098 | 0.19896 | 0.112281 |
| $A_6$ | 0.110329 | 0.347571 | 0.173198 | 0.149486 | 0.088697 | 0.111964 | 0.221849 | 0.089405 |
| $A_7$ | 0.104013 | 0.535923 | 0.158725 | 0.119031 | 0.13935 | 0.111964 | 0.147938 | 0.144405 |

Table 14. Distance values.

| | $C_1$ | $C_2$ | $C_3$ | $C_4$ | $C_5$ | $C_6$ | $C_7$ | $C_8$ |
|---|---|---|---|---|---|---|---|---|
| $A_1$ | -0.00741 | -0.01161 | -0.0087 | 0.064264 | 0.017744 | -0.01264 | -0.05582 | 0.007164 |
| $A_2$ | 0.058835 | 0.017977 | -0.05195 | 0.033726 | 0.04946 | 0.00522 | -0.0461 | 0.055354 |
| $A_3$ | -0.00109 | -0.0905 | 0.041864 | 0.012341 | -0.00548 | 0.061809 | 0.078159 | 0.020948 |
| $A_4$ | 0.036754 | -0.00175 | 0.058707 | -0.00271 | -0.02657 | -0.02445 | 0.073582 | -0.03405 |
| $A_5$ | 0.027305 | -0.03133 | -0.02073 | -0.00271 | 0.013557 | -0.01461 | 0.009163 | -0.01118 |
| $A_6$ | -0.03886 | -0.01089 | 0.010593 | -0.02431 | -0.03924 | 0.001258 | 0.032052 | -0.03405 |
| $A_7$ | -0.04518 | 0.177461 | -0.00388 | -0.05477 | 0.011416 | 0.001258 | -0.04186 | 0.020948 |

Then we obtain the rank of the alternatives under each HyperSoft set as shown in Table 15.

Table 15. Rank of alternatives.

| | First HyperSoft | Second HyperSoft | Third HyperSoft | Fourth HyperSoft | Final |
|---|---|---|---|---|---|
| $A_1$ | 6 | 6 | 6 | 3 | 6 |
| $A_2$ | 4 | 3 | 3 | 7 | 3 |
| $A_3$ | 7 | 7 | 7 | 6 | 7 |
| $A_4$ | 5 | 5 | 4 | 5 | 5 |

| | | | | | |
|---|---|---|---|---|---|
| $A_5$ | 3 | 4 | 5 | 2 | 4 |
| $A_6$ | 2 | 1 | 2 | 1 | 1 |
| $A_7$ | 1 | 2 | 1 | 4 | 2 |

## 4. Conclusions

The evaluation of ideological and political education in colleges and universities under the background of big data presents both opportunities and challenges. While data-driven insights can significantly enhance personalized learning experiences and teaching efficiency, their effectiveness depends on a well-structured evaluation system that considers key factors such as curriculum relevance, student engagement, and technological integration. This study underscores the necessity of Multi-Criteria Decision-Making (MCDM) methodologies to systematically assess and rank educational strategies, ensuring that institutions adopt the most effective approaches.

We used the SuperHyperSoft set to deal with criteria and sub criteria. This study used eight criteria and seven alternatives to be evaluated. We divided the ranking of the alternatives into four HyperSoft sets. In each HyperSoft set we obtain the ranking of the alternatives. Then we obtain the final ranks of the alternatives. Two MCDM methods are used such as CRITIC method to compute the criteria weights and the MABAC method to rank the alternatives.

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