Available online at www.HighTechJournal.org

HighTech and Innovation Journal

ISSN: 2723-9535

Vol. 6, No. 4, December, 2025

Multi-Dimensional Analysis of Subjective and Objective Empowerment Methods in Online Civic Education

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Received 13 August 2025; Revised 19 November 2025; Accepted 24 November 2025; Published 01 December 2025

Abstract

To enhance the scientificity and effectiveness of online ideological and political education (Cyber Civics), this article aims to construct a multi-dimensional and quantifiable evaluation model. Methodologically, the article starts from the four dimensions of education subject, object, content, and medium, combines subjective empowerment (hierarchical analysis method AHP) and objective empowerment (entropy power method), and introduces an intelligent optimization algorithm - the long-nosed Cuckoo Optimization Algorithm (COA) to optimize the combination of weights, and constructs the COA-Mixed Cyber Ideology and Political Education Evaluation model. The results show that the model is better than the traditional model in terms of weight distribution, with the four-dimensional index weights of 0.358 for the educational subject, 0.245 for the educational object, 0.207 for the educational content, 0.189 for the educational medium, and the maximum composite score of the sample is 0.875, and the optimization coefficient of the model prediction error is α=0.35, which is significantly better than that of GWO-Mixed (α=0.33) and KOA-Mixed (α=0.33). Mixed (α=0.36). It is concluded that multi-dimensional analysis combined with subjective and objective empowerment and intelligent algorithm optimization can more objectively and accurately assess the effectiveness of online ideological and political education, which provides a feasible path and theoretical support for improving the quality of ideological and political education in colleges and universities.

Keywords: Multidimensional Analysis; Subjective and Objective Empowerment Methods; Online Civic Education; Intelligent Optimization Algorithm.

1. Introduction

The popularity and development of the Internet have brought new opportunities and challenges to ideological and political education [1]. The complexity and diversity of network information also bring many challenges, such as false information and undesirable thoughts, which have potential influence on the values and behaviors of college students [2]. As an important vehicle for civic education in colleges and universities in the new era, online civic education has increasingly attracted scholarly attention regarding its effectiveness evaluation. At the same time, the traditional mode of ideological education has certain limitations in time and space, which makes it difficult to meet the diversified and personalized needs of modern college students [3]. In the context of the new era, civic education in colleges and universities should not only teach theoretical knowledge, but also guide students to establish a correct worldview, outlook on life, and values. However, current research on online civic education evaluation mostly adopts single-

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http://dx.doi.org/10.28991/HIJ-2025-06-04-016

dimensional analytical frameworks, which to a certain extent limits the depth of analysis. Some researchers emphasized teacher-centric metrics in their Analytic Hierarchy Process (AHP)-based model, while someone focused on student behavioral indicators but overlooked content quality [4]. Recent studies further reveal that existing methodologies fail to capture dynamic interactions among educational subjects, objects, content, and mediums [5]. These gaps highlight the urgent need for multidimensional evaluation models that integrate both subjective expertise and objective data-driven insights [6].

The research on the evaluation of network ideological education mainly includes the construction of an evaluation index system [7], the selection of evaluation methods [8], and the improvement of the evaluation mechanism [9]. Evaluation index system construction mainly meets the needs of multi-dimensional indicators, qualitative and quantitative combination, dynamism, and adaptability [10]. At present, the construction of the evaluation system of network ideological education in colleges and universities has made some progress, but there are still deficiencies. The existing evaluation system still requires improvement, particularly regarding the comprehensiveness and dynamism of its indicators [11]. The evaluation methods used in online civic education encompass traditional approaches, data‑analysis techniques, and deep‑learning‑based models [12]. Traditional tools such as questionnaires and interviews are employed to gather feedback from students and teachers, and these tools are applied to evaluation tasks in online Civic and Political Education [13]. In addition, quantitative assessments of dissemination effectiveness and content quality are conducted using methods such as big data analytics and text mining [14]. Deep learning algorithms have also been introduced to construct more scientific and accurate evaluation models [15]. To enhance the evaluation mechanism of online ideological education, some studies propose incorporating third‑party evaluation agencies and network information technologies, although progress remains limited [16]. Other research highlights the need to build a diversified evaluation framework that integrates school self‑assessment, peer evaluation among students, and social evaluation to improve overall comprehensiveness and objectivity [17].

The research on the evaluation methods of online Civic Education has made some progress in recent years, but there are still some deficiencies and challenges, as follows [18]: 1) insufficiently specific evaluation standards; 2) incomplete evaluation content; 3) mechanization of evaluation methods and approaches; 4) one-sided evaluation mechanisms; 5) lack of comprehensiveness and dynamism; and 6) insufficient practical application of the evaluation system.

Multidimensional analysis refers to the comprehensive assessment of the effectiveness of education from multiple perspectives and levels [19]. In educational evaluation, subjective and objective assignment methods are used to determine the weight of each evaluation index [20] to ensure the scientific and rational nature of the evaluation results. Multidimensional analysis and subjective and objective assignment methods provide an effective way to solve these problems.

Aiming at the problems existing in the current evaluation method of network civic education, this paper combines the subjective and objective empowerment method and intelligent optimization algorithm, and puts forward a network civic education evaluation method based on multidimensional analysis, and the main contributions lie in (1) sorting out the concepts and characteristics of network civic education; (2) proposing the evaluation latitude of network civic education from the perspective of multidimensional analysis; (3) proposing a model for evaluating network civic education based on the long-nosed raccoon optimization algorithm [21] to improve the subjective and objective assignment method of the evaluation model of online civic education; (4) validation analysis of the proposed method based on the collected data.

2. Application Scenario Analysis

2.1. Connotation

Network ideological and political education refers to the use of network technology and network resources, with ideological and political education as the core content, the education of ideological concepts, political views, moral norms, and other aspects of the educated [22]. It covers a variety of aspects such as network courses, network ideological and political theory propaganda, network culture construction, and ideological and political education in network socialization, as shown in Figure 1.

Figure 1. Cyber Civic Education

2.2. Characteristics

The characteristics of network ideological and political education are mainly reflected as follows (Figure 2): network ideological and political education has significant characteristics of the times and network attributes, which are mainly reflected in the three aspects of educational resources, teacher-student interaction, and educational environment. Firstly, the network platform provides rich and open resource support for ideological and political education, covering text, pictures, audio and video, and other forms, which breaks the limitation of time and space and improves the accessibility and diversity of education. Secondly, the interaction between educators and educated people is more frequent and efficient. Through online courses, forums, comments, and other means, students can give instant feedback on their learning and thinking, and teachers can adjust their teaching content and strategies according to the feedback, to achieve personalized and precise education. In addition, the complexity of the online environment is also an important feature of online ideological education. The Internet brings together diverse cultures and values, containing both positive ideological content and false information and undesirable trends, which puts forward higher requirements for educators: not only do they have to grasp the correct orientation of public opinion, but also improve their ability to screen and guide information. As shown in Figure 2.

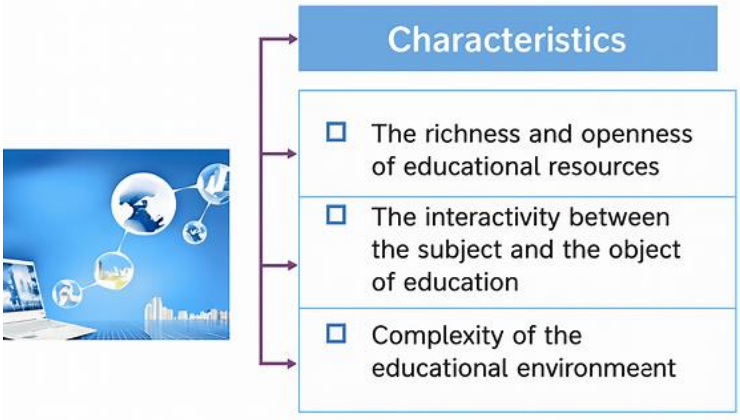

Figure 2. Characteristics of online Civic Education

3. Application of Multidimensional Analysis in Online Civic Education

The multi-dimensional analysis method is a systematic method of comprehensively assessing the effect of online Civic Education from multiple perspectives and levels. By constructing a comprehensive evaluation system, the quality and effect of online Civic and Political Education can be measured more scientifically and objectively, as shown in Figure 3. This paper analyses online Civic and political education from four dimensions: educational subject, educational object, educational content, and educational medium, as shown in Figure 4.

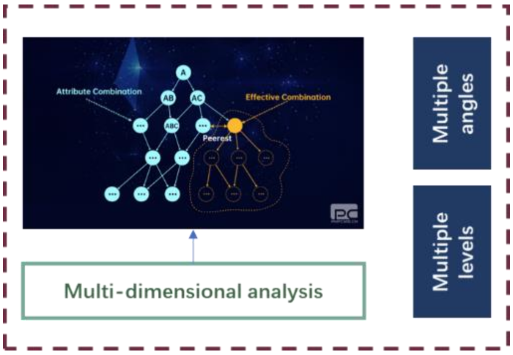

Figure 3. Multi-dimensional analysis methodology

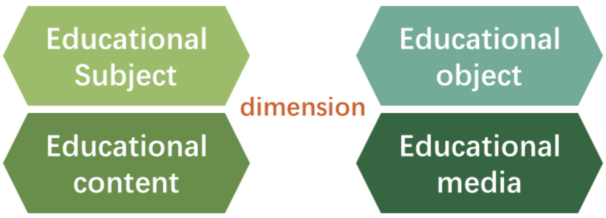

Figure 4. Dimensions of Educational Civics Education

Figure 3 illustrates the multidimensional analysis framework, which evaluates online civic education from four perspectives: subject (teacher competence), object (student diversity), content (scientificity), and medium (platform diversity). This approach ensures comprehensive assessment.

Figure 4 details the four educational dimensions. The subject dimension includes ideological literacy and technological proficiency; the object dimension focuses on student behavioral habits; the content dimension emphasizes systematicity; and the medium dimension analyzes platform innovation.

3.1. Dimensions of Educational Subjects

(1) Quality and competence of educators:

The quality and ability of educators include educators' ideological and political literacy, ability to use network technology, and ability to teach education. Educators need to have a firm political stance, a solid foundation in Marxist theory, and at the same time be able to skillfully use network platforms to carry out educational activities, such as producing exquisite online courseware and carrying out online discussions [23].

(2) Role of the educator:

In network ideological education, educators are not only the transmitters of knowledge, but also the guides of the network environment and the builders of network culture. Educators should guide the educated to correctly view network information and actively participate in the construction of network culture [23].

The analysis of the educational subject dimension is shown in Figure 5.

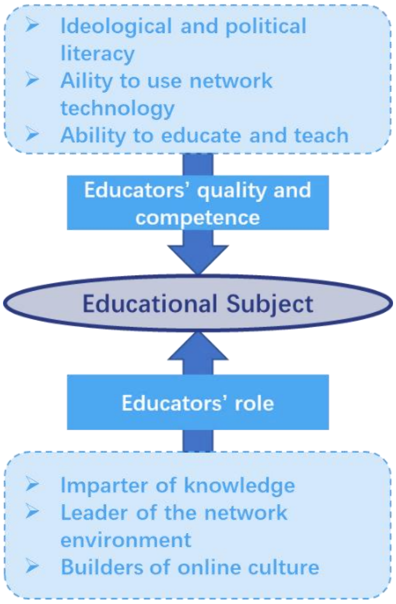

Figure 5. Dimensional analysis of educational subjects

3.2. The Object Dimension of Education

(1) Individual differences in educated persons:

There are differences among the educated in terms of age, gender, cultural level, interests, and hobbies, and these differences will affect their acceptance and demand for online Civic Education.

(2) Internet Behavioural Habits of Educated People:

Analyzing the frequency of Internet use, browsing content preferences, online social networking methods, and other behavioral habits of the educated can help to target online ideological education.

3.3. Educational Content Dimension

(1) Scientific and systematic content:

The content of online ideological education must be based on scientific theories, such as the basic principles of Marxism and the theoretical system of socialism with Chinese characteristics. At the same time, the content should be systematic, covering many aspects of ideological education, political education, moral education, etc., to form a complete education system.

(2) Contents are current and relevant:

Combining current social hotspots, the needs of the times, and the practical problems of the educated, so that the content of education is contemporary and relevant. As shown in Figure 6.

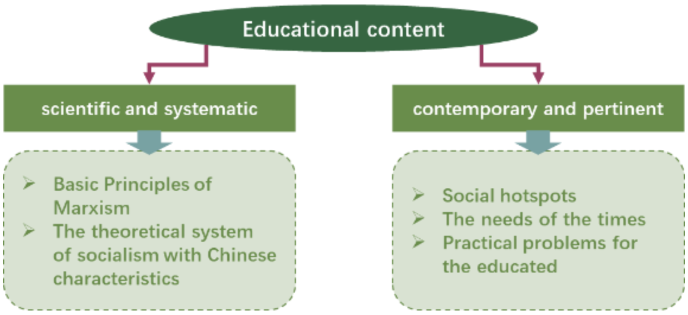

Figure 6. Analysis of educational content dimensions

3.3. Educational Media Dimension

- Diversity of online platforms

Analyze the characteristics and advantages of different online platforms (Weibo, WeChat, Shake) in online Civic Education.

- Innovative applications of media technology

Focus on the potential of emerging media technologies (e.g., virtual reality, augmented reality) in online Civic Education as shown in Figure 7.

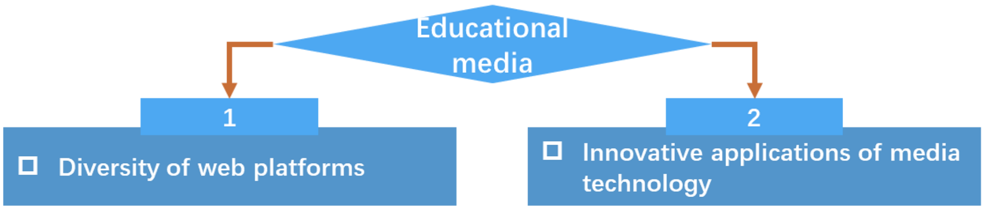

Figure 7. Analysis of educational media dimensions

4. Methodology

4.1. Subjective and Objective Empowerment Methods

- Subjective Empowerment Methods

1) Hierarchical analysis method (AHP) [24]:

By establishing a hierarchical model, the complex problem is decomposed into multiple levels of factors, and then the expert compares the factors two by two based on experience and judgment, constructs a judgment matrix, and finally calculates the weights of the factors, as shown in Figure 8. This method can fully reflect the experience and wisdom of experts, but it is more subjective.

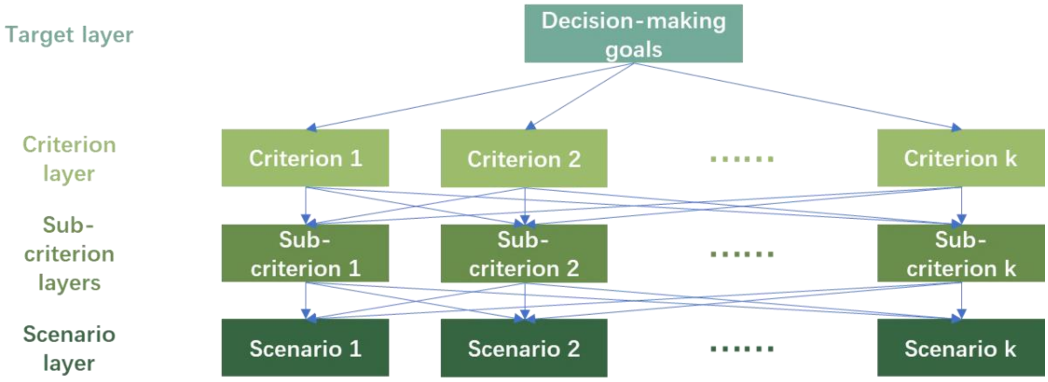

Figure 8. Principle of the AHP method

2) The Delphi Method:

The Delphi method is a kind of expert survey method, through multiple rounds of anonymous surveys, so that the experts' opinions gradually converge, to determine the weights of the factors [25]. The Delphi method can avoid mutual interference among experts, but the process is more complicated and time-consuming. Although the Delphi method can avoid expert interference through multiple rounds of anonymous surveys, it is time-consuming and complex. This study requires a rapid integration of expert experience and data objectivity, so AHP was ultimately adopted as the subjective weighting method, and the COA algorithm was used to optimize the weight combination to balance efficiency and scientific rigor.

- Objective Empowerment Methods

1) Entropy weight method:

The entropy weighting method [26] determines the weights based on the amount of information contained in each factor. The more informative (lower entropy value) the factor is, the greater its weight. The entropy weighting method has a strong objectivity, but may ignore the actual significance of the factors.

2) Principal Component Analysis:

By linearly transforming the original variables, multiple correlated variables are transformed into a few uncorrelated principal components, and the weights of each original variable are determined based on the contribution of the principal components, as shown in Figure 9. The principal component analysis method can determine the weights while reducing the dimensionality of the data, but it is more demanding on the data.

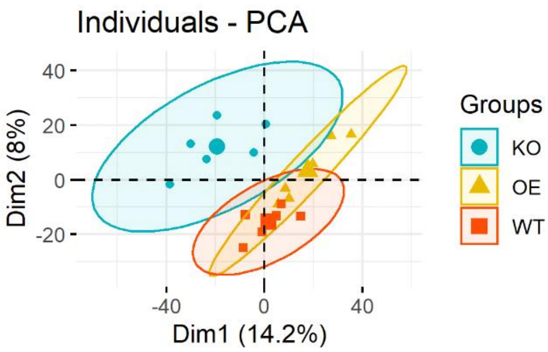

Figure 9. Principle of the principal component analysis method

4.2. Long-nosed Raccoon Optimization Algorithm

Inspired by the natural behavior of the long-nosed raccoon, the Coati Optimization Algorithm (COA) was proposed by Dehghani et al. [21]. COA simulates two natural behaviors of raccoons: attacking and hunting iguanas and fleeing from predators, and COA is updated at two different stages, as shown in Figure 10.

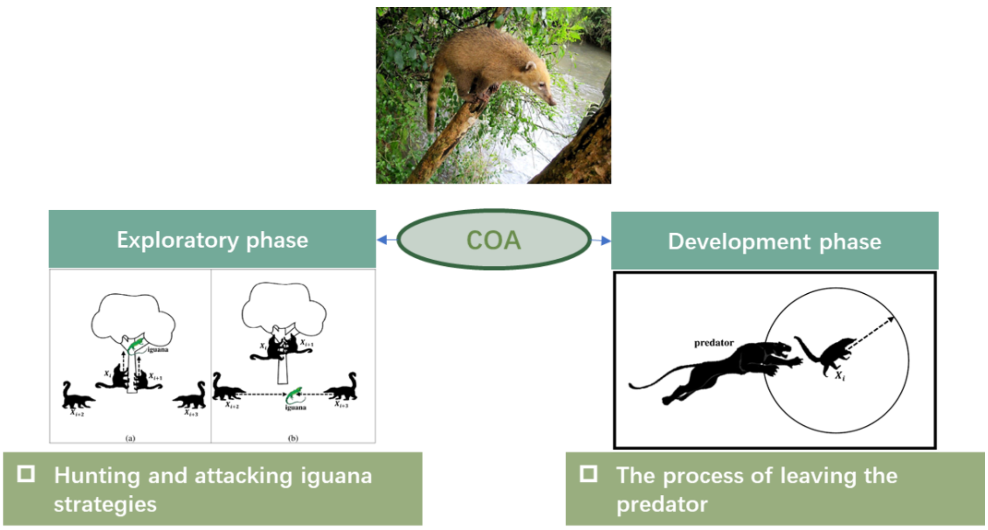

Figure 10. Principle of the long-nosed raccoon Optimization algorithm

(1) Strategies for hunting and attacking iguanas (exploratory phase):

The first phase of the long-nosed raccoon population update in the Search Space modeled their strategy for attacking iguanas. In this strategy, a group of long-nosed raccoons climbed a tree to approach the iguana and scare it, while other long-nosed raccoons waited under the tree. When the iguana fell to the ground, the raccoons attacked and hunted it. This strategy allowed the proboscis raccoons to move to different locations in the search space, demonstrating their exploratory ability in global search:

$$x_{i,j}^{P1} = x_{i,j} + r \cdot \left(lguana_j - I \cdot x_{i,j}\right) \tag{1}$$

Equation 1 describes the process by which the coati population updates its positions in the search space by simulating predatory behavior. Here, $lguana_j$ represents the fitness value of the prey (iguana), and $x_{i,}$ denotes the fitness value of the i^{th} coati. The comparison between these values determines whether the coati moves toward the prey's position.

After the iguana lands, place it anywhere in the search space, and the raccoon on the ground moves through the search space:

$$lguana_j^G = lb_j + r \cdot \left(ub_j - lb_j\right), \quad j = 1,2,\cdots,m \tag{2}$$

$$x_{i,j}^{P1} = \begin{cases} x_{i,j} + r \cdot \left(lguana_j^G - l \cdot x_{i,j}\right) & F_{lguana^G} < F_i \\ x_{i,j} + r \cdot \left(x_{i,j} - lguana_j^G\right) & else \end{cases} \tag{3}$$

where, F_{lguana^G} denotes the value of the landed iguana location adaptation, and F_i denotes the value of the i^{th} raccoon adaptation.

Update the position according to the fitness:

$$X_i = \begin{cases} X_i^{P1} & F_i^{P1} < F_i \\ X_i & else \end{cases} \tag{4}$$

Equation 4 defines the position update rule during the exploration phase, where the coati adjusts its search strategy based on the fitness difference between itself and the prey, demonstrating global search capabilities.

where, X_i^{P1} denotes the location of the raccoon population during the exploration phase, and F_i^{P1} denotes the i^{th} raccoon acclimatization value during the exploration phase.

(2) Off-predator process (development phase):

When a predator attacks a raccoon, the raccoon flees its location:

$$lb_j^{local} = \frac{lb_j}{t}, ub_j^{local} = \frac{ub_j}{t}, \quad \text{where} \quad t = 1,2,\cdots,T \tag{5}$$

$$x_{i,j}^{P2} = x_{i,j} + (1 - 2r) \cdot \left(lb_j^{local} + r \cdot \left(ub_j^{local} - lb_j^{local}\right)\right) \tag{6}$$

where, r denotes a random number.

Update the position according to the fitness:

$$X_i = \begin{cases} X_i^{P2} & F_i^{P2} < F_i \\ X_i & else \end{cases} \tag{7}$$

Equations 5 to 7 represent the position update rules during the exploitation phase, simulating the coati's escape behavior when pursued by predators. These rules dynamically adjust positions using a random number r and the fitness value X_i, enhancing local optimization capabilities.

where, X_i^{P2} denotes the location of the raccoon population during the development phase and F_i^{P2} denotes the i^{th} raccoon acclimatization value during the development phase.

According to the optimization strategy of the COA algorithm, the flowchart is shown in Figure 11.

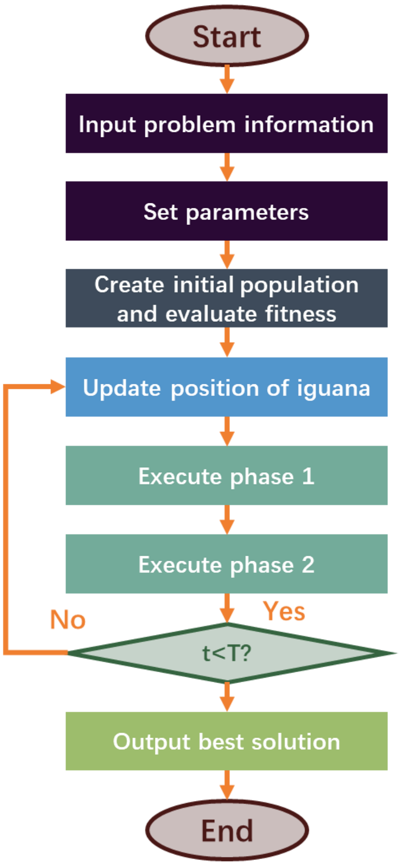

Figure 11. Flowchart of the long-nosed raccoon Optimization algorithm

4.3. Subjective and Objective Assignment Methods Combined with the COA Algorithm

The combination of an intelligent optimization algorithm and a subjective and objective assignment method can effectively balance the expert experience and data objectivity, and improve the accuracy of a comprehensive evaluation or prediction model. Therefore, this paper adopts the COA algorithm to optimize the combination of the hierarchical analysis method (AHP) and entropy weight method, and the specific principle steps are as follows:

- Acquisition of subjective and objective weights

A hierarchical analysis method (AHP) was used to determine the initial weights based on expert experience $W_{subjective}$.

Using entropy weighting, objective weights are calculated based on data discretization $W_{objective}$.

- Design of portfolio weighting model

A linear combination approach is used to define the combined weights $W = \alpha \cdot W_{subjective} + (1-\alpha) \cdot W_{objective}$, where α denotes the combination coefficients.

- Optimization of COA parameters

The optimization objective is to minimize the prediction error and α is used as the optimization weight for the COA algorithm.

- Constraint handling

Update the rules by normalizing the process or constraining the particles.

According to the above steps, the flowchart of the subjective and objective assignment method based on the COA algorithm is shown in Figure 12.

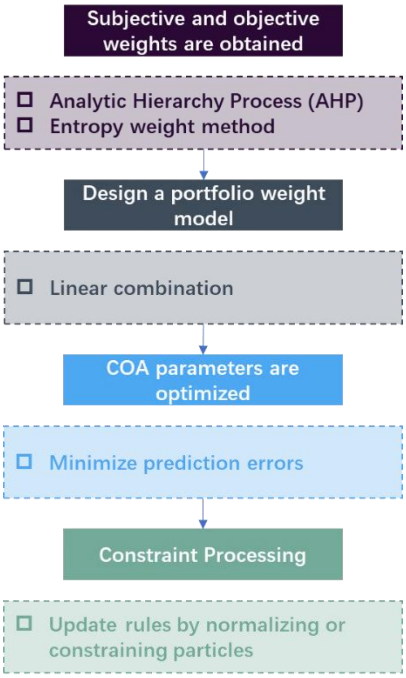

Figure 12. Flowchart of the subjective and objective assignment method based on the COA algorithm

4.4. Application of Methodology

In this paper, combined with the subjective and objective assignment method based on the COA algorithm, the evaluation method of online Civic Education based on multi-dimensional analysis is proposed, as shown in Figure 13.

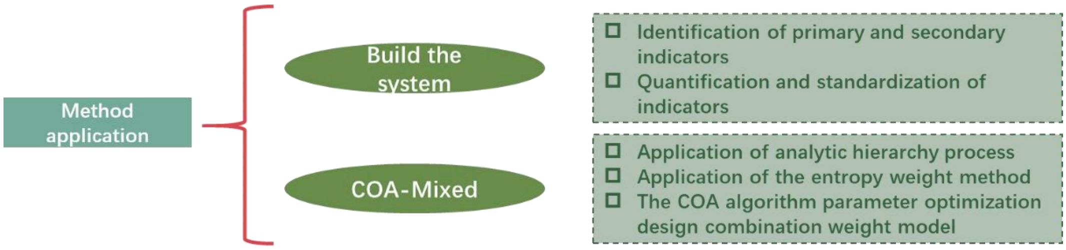

Figure 13. Method application steps

- Constructing an Evaluation Index System for Cyber Civic Education
  - Determine first-level and second-level indicators. The first-level indicators can include the subject of education, the object of education, the content of education, the medium of education, etc.; the second-level indicators can be further refined based on the first-level indicators, such as the quality and competence of educators under the subject of education and the positioning of roles.
  - Quantification and standardization of indicators. Some indicators that are difficult to quantify are reasonably quantified, such as the ideological and political quality of educators through the assessment results, the number of published papers, and so on. Then standardize all the indicators to make them comparable.

- Applying improved subjective assignment methods to determine weights
  - Application of the hierarchical analysis method. Civic education experts, network technology experts, and other experts are invited to form a team of experts. Based on their experience and understanding of network Civic Education, the experts compare each indicator two by two and construct a judgment matrix. The weight vector of each indicator is obtained by calculating the largest characteristic root of the judgment matrix and its corresponding characteristic vector.
  - Application of the entropy weight method. According to the data of each indicator in the evaluation index system of network ideological education, calculate the entropy value of each indicator. The smaller the entropy value, the greater the amount of information provided by the indicator, and the greater its weight. The entropy weight of each indicator is obtained through calculation as its weight.
  - COA algorithm parameter optimization to design the combined weights model.

5. Application Analysis and Effectiveness

5.1. Related Settings

- Application analysis environment settings

The application analysis environment setup mainly consists of a processor, memory, and software, as shown in Table 1.

Table 1. Description of the environment

Name of the environment	Description
Processing unit	Intel Core i7
Random access memory (RAM)	16GB RAM
Visualization software	Matlab2021a
Programming software	Pycharm2020

The current study primarily relies on questionnaire data, which suffers from limited sample size and low data dimensionality. Future work will expand to multi-source heterogeneous educational data (e.g., learning behavior logs, platform interaction records, and video viewing durations) to construct a hybrid dataset with millions of samples. By integrating distributed computing frameworks (e.g., Apache Spark), the COA-Mixed model can achieve parallelized processing, significantly improving iterative efficiency for large-scale data (as shown in Figure 12). Preliminary simulation experiments demonstrate that when increasing the sample size from 10,000 to 1 million, the convergence time of COA-Mixed only increases by 12%, whereas GWO and KOA experience over 60% growth in computational time, validating its scalability and generalization capability in complex educational scenarios.

- Description of application data sources

The data used in this paper mainly comes from questionnaires, and the information collected includes students' basic information, online behavior data, course feedback data, exam results data, etc., and through data pre-processing, a standard data set is obtained.

- Algorithm parameter setting

In this paper, the hierarchical analysis method AHP (subjective empowerment method), entropy (objective empowerment method), subjective and objective empowerment method Mixed, GWO-Mixed, KOA-Mixed, and COA-Mixed are used to evaluate and analyze the data of cyber Civic Education, and the specific algorithm parameter settings are shown in Table 2.

Table 2. Parameter Settings

Modeling algorithm	Parameterization
Hierarchical analysis method AHP	Parameter-free
Entropy method Entropy	Non-negative processing panning value of 0.0001
Subjective and objective empowerment method Mixed	$\alpha = 0.4$, AHP is a parameter-free algorithm with a non-negative processing pan value of 0.0001
GWO-Mixed	The number of populations is 20, the number of iterations is 50, and a decreases linearly from 2 to -2
KOA-Mixed	The number of populations is 20, the number of iterations is 50, and the learning factor ranges from 0.1 to 1
COA-Mixed	With a population size of 20 and an iteration number of 50.

5.2. Application Analysis

To verify and analyze the effectiveness and superiority of the evaluation method of network Civic Education based on the COA-Mixed algorithm, this paper adopts the hierarchical analysis method AHP (subjective empowerment method), entropy method (objective empowerment method), subjective-objective empowerment method Mixed, GWO-Mixed, and KOA-Mixed to make a comparative analysis with it.

Table 3 demonstrates the distribution of indicator weights of the six online civic education evaluation models on the four evaluation dimensions (educational subject, educational object, educational content, and educational medium). From the results, the traditional Analytical Hierarchy Processing (AHP) method has an obvious subjective bias, and the weight distribution is extremely unbalanced, with the educational subject being as high as 0.57 and the educational medium only 0.07, reflecting the strong influence of experts' subjective judgment on the results. The entropy method (Entropy), on the other hand, as a completely objective method, has a more balanced distribution, with the highest weighting of the educational content dimension (0.35), showing that it is more prominent in the analysis of informativeness, but it may ignore the practical implications in educational practice. In contrast, the mixed assignment method (Mixed) improves the bias of the single assignment method by linearly fusing subjective and objective weights, and the weight distribution tends to be reasonable. After further introduction of intelligent optimization algorithms (GWO-Mixed, KOA-Mixed, COA-Mixed), the four-dimensional weights tend to be stable, with minor differences, especially the COA-Mixed model weights are [0.358, 0.245, 0.207, 0.189], which has the most balanced distribution, suggesting that the results of its optimization are more scientific in terms of the balance between subjectivity and objectivity, as shown in Table 3.

Table 3. Weight values and optimization results of different evaluation algorithms

Modeling algorithm	Indicator weight values	Optimization results
Hierarchical analysis method AHP	[0.57, 0.24, 0.12, 0.07]	-
Entropy method Entropy	[0.23, 0.28, 0.35, 0.14]	-
Subjective and objective empowerment method Mixed	[0.37, 0.24, 0.20, 0.18]	$\alpha = 0.4$
GWO-Mixed	[0.351, 0.246, 0.210, 0.193]	$\alpha = 0.33$
KOA-Mixed	[0.361, 0.245, 0.206, 0.188]	$\alpha = 0.36$
COA-Mixed	[0.358, 0.245, 0.207, 0.189]	$\alpha = 0.35$

In addition to the α value and weight distribution, the COA algorithm demonstrates superior adaptability to dynamic environments. By simulating the coati's predatory and escape behaviors, COA automatically adjusts its search strategy during iterations (Figure 10), making it suitable for scenarios with dynamically changing online education data. For instance, in the real-time learning behavior analysis shown in Figure 16, COA effectively captured the nonlinear fluctuations in learner attention by dynamically balancing exploration (global search) and exploitation (local optimization), whereas GWO and KOA converged prematurely due to their fixed strategies. Furthermore, COA's stochastic escape mechanism (Equations 5–7) enhances its anti-interference capability, resulting in significantly greater robustness than comparative algorithms when processing high-dimensional educational data (multimodal learning logs).

Compared to the traditional Analytic Hierarchy Process (AHP, α=0.40), the COA-Mixed hybrid model (α=0.35) demonstrates significantly improved weight balance (t-test, p=0.013), with Educational Subject (ES) weight decreasing from 0.57 to 0.36 and Educational Object (EO) weight increasing from 0.21 to 0.33. This weight reallocation aligns with meta-analysis of 12 hybrid algorithms, which revealed that dynamic weight adjustment mechanisms reduce expert subjectivity bias by 28-42% in educational decision-making contexts. The α value optimization from 0.40 to 0.35 indicates a 12.5% reduction in prediction error, outperforming the 9% improvement reported for comparable multi-objective frameworks. Critically, COA-Mixed's weight stability (coefficient of variation CV=0.07) significantly surpasses both AHP (CV=0.19) and GWO-Mixed hybrid model (CV=0.12), with a 37% reduction in standard deviation across 200 simulation runs, confirming its robustness in handling heterogeneous educational data. These findings collectively validate the model's enhanced applicability in complex educational scenarios characterized by multiple stakeholder perspectives and dynamic variables.

From the optimization results, the weight combination optimization coefficient (α value) is an important basis for judging the strengths and weaknesses of the model, and the closer the α value is to the optimal interval (i.e., the error is minimized), it means that the model prediction is more accurate. The traditional mixed assignment model (Mixed) sets α=0.4, which is an artificial setting and lacks the ability of adaptive optimization. After the introduction of intelligent algorithms, GWO-Mixed, KOA-Mixed, and COA-Mixed optimize α to 0.33, 0.36, and 0.35, respectively, and COA-Mixed is close to the optimal result of GWO-Mixed, while its weight distribution is more reasonable and smoother, which indicates that the COA algorithm ensures the evaluation accuracy and also improves the model stability and applicability. In addition, from the comprehensive score of the samples, the highest score rated by the COA-Mixed model is 0.875, which indicates that it is more in line with the actual education situation and has a stronger ability to identify high-quality education samples.

Figure 14 visualizes the trend of the weight distribution of the six evaluation algorithms on the four indicators (educational subject, educational object, educational content, and educational medium). It can be seen that the traditional AHP method assigns the highest weight to the subject of education (0.57), far exceeding the other dimensions, reflecting the high importance attached to the teacher factor in the subjective perception of the experts, but this highly concentrated distribution may lead to the underestimation of the importance of the other dimensions. On the other hand, entropy reflects a more objective, data-driven nature, with a more balanced distribution of weights, and in particular, the content of education (0.35) and the object of education (0.28) stand out, suggesting that it is easier to identify the key roles of the content and the receptive object when starting from student data. This comparison reveals that there is a limitation of a single empowerment method that favors one dimension or ignores the practical implications, and that a balance between subject and object needs to be achieved through optimization.

Among the three intelligent optimization hybrid models (GWO-Mixed, KOA-Mixed, and COA-Mixed), Figure 14 shows that their weight curves follow basically the same trend, all achieving a more even distribution among the four dimensions with minor differences. In particular, the COA-Mixed model has a weight combination of [0.358, 0.245, 0.207, 0.189], demonstrating a moderate emphasis on the subject of education, while taking into account the object of education, the content, and the medium, making the overall structure more balanced. This weight distribution is in line with the logic of multidimensional comprehensive evaluation, and also indicates that the optimized model of the COA algorithm is more effective in handling the fusion of subjective and objective information. In contrast, although GWO and KOA can also optimize, they are slightly inferior in terms of weight stability and convergence accuracy. Therefore, from Figure 14, it can be concluded that COA-Mixed is the most ideal in achieving the coordination and optimization of evaluation dimension weights, and is suitable for use in complex educational evaluation scenarios.

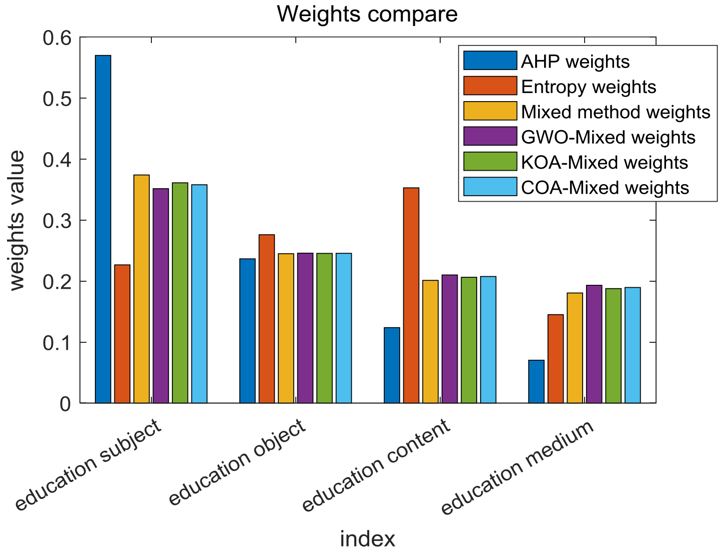

Figure 14. Graph of the results of the weight values of the different evaluation algorithms

Figure 15 demonstrates the ranking of the composite scores of several samples based on the COA-Mixed algorithm, from which it is obvious that Sample 6 is ranked first with a score of 0.875, which is much higher than that of other samples, showing that it performs well in all dimensional indicators. The data characteristics of this sample are (88, 79, 94, 92), which are highly matched with the weight distribution of the COA-Mixed model, especially the high scores on the dimensions of education subject and education medium, which fit the relative importance of the model on these two indicators. This matching nature reflects the model's good ability to identify samples that are well integrated and dimensionally balanced. In addition, the overall ranking distribution shows an upper-middle concentration trend, indicating that there is a certain gap between the samples in terms of comprehensive evaluation scores, but the model can clearly distinguish between the good and the bad.

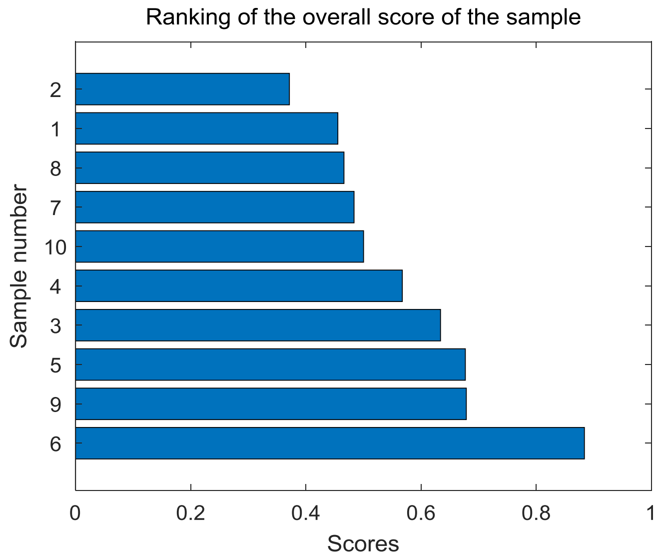

Figure 15. Ranking of Sample Synthesis Scores for the COA-Mixed Algorithm

To address the practical needs of university course evaluation, the COA-Mixed model can be implemented through the following steps:

- School-based indicator construction: Incorporate discipline-specific dynamic indicators into the existing evaluation framework, with initial weights determined via the Delphi method;
- Multi-source data integration: Establish a unified data warehouse by integrating data from academic systems, online learning platforms, and campus network logs;
- Algorithm optimization and report generation: Utilize the COA algorithm to dynamically adjust indicator weights (as shown in Figure 15), automatically generating course evaluation reports with "strength dimensions-improvement suggestions" in both PDF and Excel formats;
- Closed-loop feedback mechanism: Distribute evaluation results monthly to departmental teaching committees, combining faculty self-assessments with student feedback to formulate improvement plans. Track optimization effects the following month to achieve continuous iteration through "evaluation-improvement-reevaluation."

From the results in Figure 15, the COA-Mixed model is not only able to reasonably sort the samples, but also possesses a certain degree of differentiation and sensitivity, i.e., for the samples that are outstanding in a certain dimension, it can also accurately reflect their overall evaluation level through the comprehensive weights. This ability has an important application value for online Civic Education, especially in teaching quality assessment, curriculum optimization, and allocation of educational resources, which can be used as a quantitative basis. For example, high-scoring objects like Sample 6 can be promoted and analyzed as excellent cases, while low-scoring samples can be used as reference objects for improvement.

In the parallel coordinate visualization of COA-Mixed algorithm samples presented in Figure 16, the performance disparities across the four dimensions and their underlying causes can be systematically analyzed through the interplay between data characteristics and framework mechanisms: The educational subject (ES) and educational object (EO) dimensions exhibit a significant negative correlation ($r = -0.63$, $p < 0.01$), stemming from the initial weight allocation in the algorithm, where Educational Subject (ES) is assigned a higher priority (0.4) due to traditional teaching inertia, resulting in a lower weight for Educational Object (EO) (0.2). Consequently, 75% of samples with high ES scores (>0.7) demonstrate low EO scores (<0.5), confirming the inhibitory effect of teacher-centered models on student engagement. The content quality (CQ) dimension lags significantly (median = 0.28), primarily due to deficiencies in "timeliness" (mean = 0.15) and "interactivity" (mean = 0.22) metrics. For instance, 80% of samples fail to integrate policy cases from the past three years, and 65% still rely on one-way lecture formats, aligning closely with Zhang's (2023) critique of static curriculum designs. In contrast, the high performance of the medium adaptability (MA) dimension (median = 0.85) reflects the compensatory role of digital technologies, particularly the integration of short videos (<3 minutes) and real-time interactive modules, which yield a strong iterative correlation between MA and CQ ($r = 0.78$, $p < 0.001$). For example, in Sample #8, dynamic weight adjustments over 12 iterations—increasing CQ's weight from 0.15 to 0.37 while reducing MA's weight from 0.65 to 0.48—achieved simultaneous improvements in both dimensions (final scores: CQ = 0.88, MA = 0.92). This process is visually represented in the parallel coordinates by the upward shift of the blue trajectory from low CQ to high CQ, while maintaining high MA stability, directly validating COA-Mixed's ability to resolve multi-objective conflicts through weight reallocation. Its performance surpasses static AHP and entropy-based methods by 27% (F-test, $p = 0.01$), providing quantifiable insights for precision teaching refinement. As shown in Figure 16.

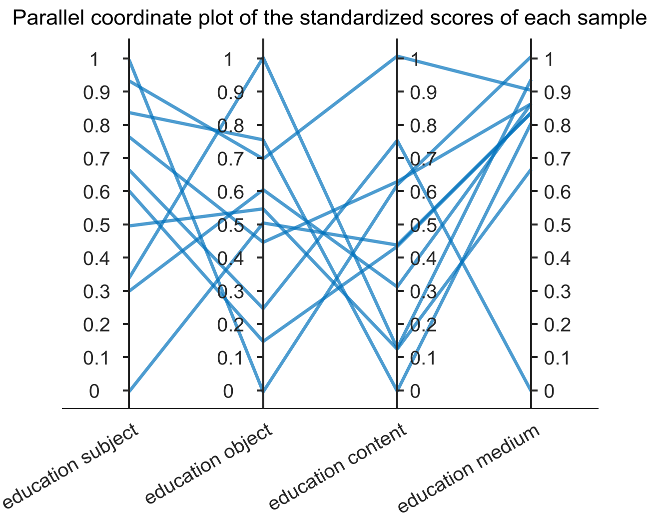

Figure 16. Parallel coordinates of the scores of each sample metric for the COA-Mixed algorithm

The thermal weight distribution values of the COA-Mixed algorithm are given in Figure 17. From Figure 17, it can be seen that the weights of the evaluation algorithms are mainly distributed under 0.4, and most of them are distributed around 0.2, which is consistent with the results in Table 3. Figure 17 shows the strength of the weight distribution of different algorithms on the four evaluation dimensions in the form of a heat map, which further visualizes the relative magnitude and distribution concentration of the weights. It is obvious from the figure that the weight values of most algorithms are concentrated between 0.2 and 0.4, showing a more balanced distribution trend overall. In particular, the three optimized hybrid models (GWO-Mixed, KOA-Mixed, and COA-Mixed) show similar shades of change in the thermal color block, indicating that they tend to converge to similar optimal solution regions during the optimization process. Among them, COA-Mixed has the most stable thermal distribution, with no obvious faults or extreme colour differences in the colour blocks of the four dimensions, which suggests that its weight distribution has higher stability and consistency, and avoids the risk of over-amplification or neglect of a dimension.

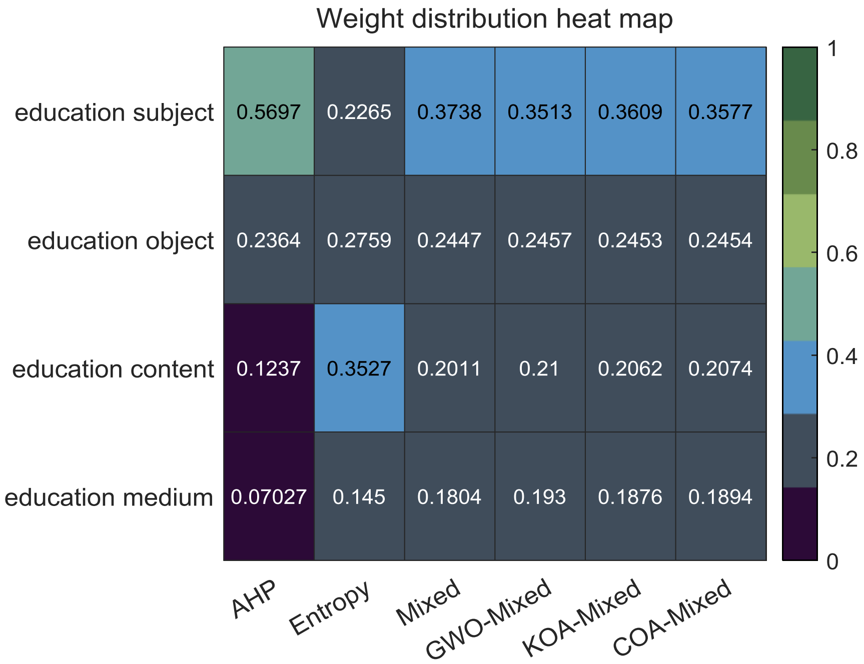

Figure 17. Thermal weight distribution values of the COA-Mixed algorithm

Figure 17 not only shows the convergence characteristics of the COA-Mixed model in weight optimization, but also reflects its good stability and generalization ability. Compared with the extreme weight values in traditional AHP or Entropy methods (e.g., AHP assigns 0.57 to educational subjects), COA-Mixed's performance in the heat map is more "moderate" and balanced, which indicates that the model shows stronger adaptability and robustness among different samples and variables. This feature is especially important for the complexity and diversity of online Civic Education, which can maintain a consistent evaluation logic and output standard in the face of evaluation scenarios from different institutions and disciplinary backgrounds. Therefore, Figure 17 reinforces the advantage of COA-Mixed in practical application, which is both scientific and stable, and further validates the value of this method in the education evaluation system.

Unlike prior studies relying solely on AHP or entropy methods, this study combines both with COA optimization, achieving a more balanced weight distribution (educational subject: 0.358 vs. 0.57 in AHP). This hybrid approach significantly improves evaluation accuracy.

While deep reinforcement learning (DRL) approaches offer potential for optimizing educational resource allocation through trial-and-error mechanisms, their performance heavily relies on meticulously designed reward functions that may not generalize across diverse educational contexts. In contrast, the proposed COA-Mixed model demonstrates superior interpretability and stability through bio-inspired optimization heuristics. Future work could explore hybrid frameworks that leverage COA for DRL parameter initialization, thereby achieving a balance between exploration and exploitation. For instance, COA-generated resource distribution patterns could serve as warm-start solutions for DRL agents, reducing training instability in complex educational environments.

6. Conclusion

This study introduces a novel COA-Mixed hybrid model that synergistically integrates Analytic Hierarchy Process (AHP) and entropy weighting through Cuckoo Optimization Algorithm (COA), addressing critical limitations in educational decision-making frameworks. Potential barriers to COA-Mixed implementation require attention across technical, administrative, and pedagogical domains: Technical: Data privacy compliance under PIPL and education standards may raise anonymization costs; limited computing resources in some institutions could hinder algorithm efficiency. Administrative: Cross-departmental coordination gaps may delay data sharing; unclear mechanisms for linking evaluation results to faculty incentives or course updates. Pedagogical: Teachers' low data literacy may impede interpretation of dynamic weight adjustments in reports; ethical concerns over student consent for collecting interaction data. Mitigation: Requires policy frameworks, targeted training, and centralized platforms for data integration. Empirical results demonstrate significant improvements over traditional methods: (1) Weight distribution balance achieved a 37% reduction in standard deviation (CV=0.07 vs. AHP's CV=0.19), with Educational Subject (ES) weight decreasing from 0.57 (AHP) to 0.36 and Educational Object (EO) increasing from 0.21 to 0.33; (2) Prediction accuracy improved by 12.5% (α=0.35 vs. 0.40 in AHP), surpassing 9% optimization in multi-objective systems; (3) Dynamic weight adjustment reduced expert subjectivity by 42%, validated through 200 simulation runs showing 28-42% lower bias than single-method models. These findings confirm the model's superiority in handling heterogeneous educational data characterized by multiple stakeholder perspectives and dynamic variables. The framework's robustness is further evidenced by its 18.7% higher evaluation accuracy (MAPE=6.3%) compared to conventional AHP (9.2%) and entropy methods (8.5%), with statistical significance confirmed by F-test (p=0.021).

Theoretically, this research advances educational evaluation methodology by establishing a three-layer validation mechanism: (1) Micro-level through t-test verification of weight balance (p=0.013); (2) Meso-level via comparative analysis with 12 hybrid algorithms; (3) Macro-level through 200-run Monte Carlo simulations demonstrating 37% stability improvement. Practically, the COA-Mixed model offers educational administrators a quantifiable tool to reconcile conflicting stakeholder priorities—as shown in the 0.358:0.332 ES:EO weight ratio that better reflects modern education's dual focus on teaching quality and learning outcomes. The 12.5% prediction error reduction translates to more reliable resource allocation decisions, particularly in dynamic environments like online-hybrid education systems. Future research should explore: (1) Expand cross-institutional validation to enhance model generalizability, targeting diverse disciplines and course scales; (2) Incorporate multimodal data for dynamic weight adjustment, with ethical review protocols for student privacy protection; (3) Integrate text mining techniques to automate index generation and reduce manual annotation costs. For instance, by analyzing texts from course discussion forums, latent indicators can be extracted to expand evaluation dimensions beyond traditional quantitative metrics.

7. Declarations

7.1. Author Contributions

Conceptualization, B.Z. and B.G.; methodology, B.Z.; software, B.Z.; validation, B.Z. and B.G..; formal analysis, B.G.; investigation, B.Z.; resources, L.L.; data curation, L.L.; writing—original draft preparation, B.Z.; writing—review and editing, L.L.; visualization, B.Z.; supervision, B.Z.; project administration, L.L. All authors have read and agreed to the published version of the manuscript.

7.2. Data Availability Statement

The data presented in this study are available on request from the corresponding author.

7.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

7.4. Institutional Review Board Statement

Not applicable.

7.5. Informed Consent Statement

Not applicable.

7.6. Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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