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A Critical Thinking Promotion Model for Ideological and Political Education Elements in EFL Classrooms Combining the Coefficient of Variation Method and Neural Networks

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Abstract This paper explores how to organically and effectively integrate ideological and political education elements into EFL classrooms and scientifically assess their promotional effects on critical thinking skills. The article first constructs an evaluation system comprising two primary indicators (skills: questioning, analysis, reasoning, judgment, evaluation; and tendencies: thinking qualities, emotional traits), seven secondary indicators, and 17 tertiary indicators. A GA-BP neural network model (input layer with 16 nodes, hidden layer with 9 nodes, and output layer with 1 node) is further constructed, using weighted indicator data as input and comprehensive evaluation values as output. Through two rounds of Delphi expert consultation, the indicators are revised, and after removing C17 "curiosity," 16 tertiary indicators are retained. Objective weighting based on the coefficient of variation method showed that critical thinking skills (A1, weight 0.672) were significantly higher than the disposition dimension (A2, weight 0.328), with "multi-angle analysis (C3, weight 0.094)" and "setting standards and comparison (C1, weight 0.085)" as core competencies. After optimizing the initial weights using a genetic algorithm, the mean squared error (MSE) of the model was reduced to 0.000682, the test set fit coefficient reached 0.999, and the prediction error was below 1.17%. Empirical analysis based on 574 valid questionnaires revealed that the average critical thinking skills scores of high-achieving students (9.10–9.87) were significantly higher than those of low-achieving students (3.56–5.42), and that average-performing students shared a common weakness in "evaluation skills (B5, 6.06 points)." Multiple regression analysis indicates that English proficiency ($\beta = 4.403$), classroom frequency ($\beta = 3.981$), and the depth of ideological and political integration ($\beta = 3.350$) are key factors promoting critical thinking ($P < 0.01$).

Index Terms course-based ideological and political education, critical thinking, coefficient of variation method, GA-BP neural network, EFL teaching

I. Introduction

"Course-based ideological and political education" aims to establish an all-encompassing educational framework that integrates all faculty, all stages of education, and all courses, ensuring that various courses are advanced in tandem with ideological and political theory courses to create a synergistic effect, thereby establishing "moral education and talent cultivation" as the core mission of education [1]. In English teaching, integrating ideological and political elements holds profound significance. It not only enhances students' moral and ideological cultivation but also strengthens cross-cultural communication, promotes innovation and development in teaching localization and ethnicization, thereby improving teaching quality and fostering students' all-round development [2]-[4]. In the new era, it is explicitly required that in EFL classrooms, value guidance and language proficiency development, along with higher-order thinking training, must each account for no less than 65% and 30% of total class hours, respectively. Bilingual classrooms can be utilized to cultivate students' critical thinking skills. During the teaching process, teachers can leverage the bilingual classroom environment and diverse teaching methods to assist students in constructing correct worldviews and value systems while enhancing their overall personal qualities and sense of social responsibility [5], [6]. By introducing course-related literature, case studies, video materials, and other resources, students can better understand national policies, laws and regulations, as well as social ethics and moral norms [7].

Bilingual classrooms encourage students to participate in discussions, debates, and expressions during classroom activities, actively respond to teachers' questions, thereby enhancing their critical thinking and communication skills, and guiding them to examine issues with a positive attitude and values, and seek solutions [8]-[11]. Additionally, through pre-class and post-class reflection questions, teachers can further stimulate students' thinking, helping them form correct ideological concepts, moral values, and a sense of social responsibility and civic consciousness [12]. In summary, integrating ideological and political elements into bilingual classrooms helps students establish a comprehensive worldview, outlook on life, and values, thereby improving their overall quality and critical thinking abilities. However, in current teaching practices, ideological and political elements are often integrated in a rigid manner, severely disconnected from English knowledge points, and with a single approach to cultivating thinking, which is not conducive to enhancing students' critical thinking abilities in EFL classrooms [13].

The coefficient of variation is a commonly used statistical method for describing the dispersion of data. It measures the dispersion of data by calculating the ratio of the standard deviation to the mean, thereby comparing the variability between different datasets [14], [15]. The dispersion of ideological and political elements in English can be calculated to facilitate the construction of an evaluation system for critical thinking skills. Neural network algorithms are a type of machine learning technology based on neural networks. They are computer models that simulate the human brain's response to external input information. They use “multi-layer weighted networks with countless learnable connection weights,” exhibiting inherent complexity. By continuously adjusting the connection weights between different layers using the backpropagation algorithm, they generate different responses based on input information, ultimately achieving relatively accurate prediction and analysis. They offer the advantages of real-time feedback and deep interaction [16]-[18]. This network model facilitates the integration of ideological and political education elements, thereby cultivating students' critical analytical abilities. The advantages of real-time feedback and deep interaction help optimize the evaluation of critical thinking abilities and stimulate students' critical thinking skills.

To organically and effectively integrate ideological and political education elements into EFL classrooms and scientifically assess their promotional effects on critical thinking abilities, this paper proposes an optimized method that integrates quantitative evaluation with intelligent prediction. First, this study systematically constructed the practical pathways for integrating ideological and political education into EFL classrooms and an evaluation system for critical thinking skills. In constructing the evaluation system, based on the intrinsic structure of critical thinking (skills and tendencies), combined with the cognitive and emotional characteristics of integrating ideological and political education into classrooms, a multi-level evaluation indicator system was systematically established, comprising five skill dimensions (“questioning, analysis, reasoning, judgment, and evaluation”) and two tendency dimensions (“thinking quality and emotional traits”). To overcome subjective weighting biases and objectively reflect the relative importance differences among evaluation indicators, this study introduced the coefficient of variation method (CVM). This method objectively weights each evaluation indicator based on the variability of its raw data (the ratio of standard deviation to mean). Indicators with higher variability indicate significant differences among samples and relatively higher implementation difficulties, thereby more objectively reflecting the actual gaps between evaluated objects. To more accurately depict the complex mapping relationship between the integration of ideological and political elements and the development of students' critical thinking, and to achieve dynamic assessment and predictive optimization of students' critical thinking abilities, this study further constructed a genetic algorithm-optimized BP neural network (GA-BP) model. This model uses the student critical thinking ability evaluation indicator data weighted by the coefficient of variation method as input and the comprehensive evaluation value as output. This study introduces the genetic algorithm (GA) to perform global optimization of the initial weights and thresholds of the BP network by simulating natural selection (selection, crossover, mutation). The genetic algorithm first generates an initial population encoded with network parameters, evaluates the quality of individuals using a fitness function, and iteratively evolves through operations such as roulette wheel selection, single-point/multi-point crossover, and non-uniform mutation, ultimately selecting the optimal initial network parameter combination. This optimization process significantly improves the convergence speed, prediction accuracy, and generalization ability of the BP neural network.

II. Pathways for integrating course-based ideological and political education and the construction of a critical thinking evaluation system

II. A. Strategies for Effectively Integrating Course-Based Ideological and Political Education into University English Classrooms

The “EFL Comprehensive” series of courses uses the Pathways series of textbooks co-published by National Geographic and Cengage Learning, focusing on cultivating students' critical thinking skills, reasoning abilities, and comprehensive English language proficiency. While using original foreign-language textbooks to teach professional knowledge and broaden students' horizons, instructors should also consider the current state of course-based ideological and political education and adopt practical strategies to effectively integrate course-based ideological and political education into university English classrooms. This approach aims to enhance students' overall English proficiency while fulfilling the educational responsibility of teaching and nurturing students.

(1) Enhance the political awareness of university English teachers and strengthen their ideological and political development.

In addition to fulfilling their primary responsibilities of "teaching, imparting knowledge, and resolving doubts," teachers also bear the important mission of educating and nurturing students. Teachers must not only continuously improve their professional skills, refine teaching methods, and impart specialized knowledge but also, in their spare time, adhere to correct ideological guidance, continuously study the Party's theoretical knowledge and policies, follow current events, enhance their Party spirit and ideological awareness, strengthen their professional ethics and ideological and political development, and integrate ideological and political learning with their teaching practice. They should serve as qualified guides on students' ideological development journey, setting a personal example, and establishing correct values. When English teachers engage with English textbooks and English-language literature, they should adopt a dialectical approach to Western culture, absorbing its essence while discarding its flaws, and enhancing their sensitivity to prevent the infiltration of Western cultural influences. Additionally, English teachers should actively study the excellent traditional culture of the Chinese nation, gain a deep understanding of Chinese culture and thought, and develop their own insights, so that they can effectively conduct ideological and political education in the classroom. Therefore, in teaching, it is not only important to emphasize the integration of Chinese and Western cultures but also to highlight and promote the excellent traditional culture of China, guiding students to firmly establish cultural confidence and cultivate a correct cultural perspective.

(2) Refine teaching objectives and internalize ideological and political elements

The primary tasks of university English teaching include enhancing students' English language proficiency, broadening their international horizons, understanding foreign cultures, and improving their cross-cultural communication skills. Teaching activities are guided by teaching objectives, which represent the expected learning outcomes for students in the teaching process. Teaching objectives are generally divided into three levels: course objectives, classroom teaching objectives, and educational development objectives. Traditional university English teaching objectives have primarily been based on teaching content, with limited emphasis on value-oriented objectives. When implementing teaching activities, teachers should refine teaching objectives to cover both teaching content and ideological and political elements, integrating ideological and political education into teaching objectives and embedding ideological and political content into teaching activities and content. This approach promotes all-round, continuous education, guiding students to understand cultural differences between China and the West, strengthening their ideological and value orientations, enhancing their ideological awareness and moral beliefs, and achieving moral education objectives to help students establish correct worldviews and value systems. While implementing ideological and political education, teachers should break away from traditional educational models, align with the trends of educational reform, and stimulate students' proactive role in ideological and political classrooms. Through innovative teaching methods, they should cultivate students' critical thinking and analytical abilities, consolidate their enthusiasm for learning, truly ignite their interest in learning, and effectively enhance their political literacy.

II. B.Evaluation indicators for students' critical thinking skills

Based on the constituent elements, structural characteristics, and cognitive and emotional features of English as a Foreign Language (EFL) classroom learning that integrates ideological and political elements, the evaluation indicators for critical thinking ability were ultimately determined, as shown in Table 1. The first-level indicators include two parts: critical thinking skills and critical thinking tendencies. These two parts are then further broken down into second-level and third-level indicators. These evaluation criteria provide valuable reference for teachers in assessing students during daily instruction. Teachers can use these criteria to focus on cultivating specific skills in students or to stimulate their critical thinking tendencies and awareness, ultimately promoting the development of their critical thinking abilities.

Table 1: Evaluation indicators of critical thinking ability in learning

Primary indicator	Secondary indicator	Tertiary indicator
A1: Critical thinking skills	B1: Questioning skills	C1: Skills for determining standards and conducting comparisons
		C2: Skills for posing questions
	B2: Analytical Skills	C3: Skills for multi-angle analysis
		C4: Skills for multi-method analysis
	B3: Reasoning Skills	C5: Skills for making assumptions about questioned content
		C6: Skills for reasoning based on assumptions about questioned content
	B4: Evaluation Skills	C7: Skills for judging the rationality and correctness of conclusions

		C8: Skills for identifying information biases and loopholes
	B5: Evaluation Skills	C9: Skills for evaluating whether something is good or badsuperior or inferior
		C10: Skills for assessing the potential risks and benefits of decisions
A2: Critical thinking tendency	B6: Thinking Quality	C11: Skills for active thinking
		C12: Skills for independent thinking
		C13: Skills for rigorous thinking
		C14: Skills for profound thinking
	B7: Emotional Traits	C15: Skills for self-confidence
		C16: Skills for boldness and courage
		C17: Skills for curiosity

II. C. Coefficient of variation method

The Coefficient of Variation Method (CVM) enables a relatively objective analysis of the content of each indicator and calculates and assigns weights to the resulting indicator weights. Its key feature is that indicators with greater variability in their values within the system are more difficult to achieve, thereby reflecting the gaps between evaluated units in a more objective manner. The specific calculation method is as follows: Suppose there are n samples, each containing m evaluation indicators; the original indicator data matrix formed is $X=\begin{pmatrix} X_1 \cdots X_m \\ \vdots \ddots \vdots \\ X_n \cdots X_{nm} \end{pmatrix}$. Then, X_{ij} represents the value of the j th evaluation indicator in the i th sample. Therefore, the formulas for the mean and standard deviation of the j th evaluation indicator are $\overline{X}=\frac{1}{n}\sum_{i=1}^{n}X_{ij}$ and $S_j=\sqrt{\frac{\sum_{i=1}^{n}\left(X_{ij}-\overline{X}_j\right)^2}{n-1}}$, respectively. In this study, the formula for the coefficient of variation of each indicator component is: $v_j=\frac{S_j}{\overline{X}_j},\left(j=1,2,\ldots,m\right)$. After normalizing the coefficient of variation, the weighting coefficient of the coefficient of variation for each indicator component is obtained as $w_j=\frac{v_j}{\sum_{j=1}^{m}v_j}$.

III. Empirical revision and weight determination of the critical thinking ability evaluation index system

Based on the exploration of strategies for integrating ideological and political education into courses and the preliminary construction of an evaluation index system for critical thinking skills that includes skill and attitude dimensions, as well as a method for weighting the index using the coefficient of variation, this study employs the Delphi expert consultation method in Chapter 3 to empirically revise the index system and determine the final weights of each level of the index using the coefficient of variation method (CVM) in order to make the evaluation system more scientific, reasonable, and standardized, and to ensure that it is in line with the actual situation of English classrooms that integrate ideological and political elements.

III. A. Revision of the Critical Thinking Ability Evaluation Index System

In order to make the preliminary critical thinking ability evaluation index system more scientific, reasonable, and standardized, the Delphi method was used to conduct expert consultations to further revise and improve the various levels of indicators.

III. A. 1) Basic Information on Experts

This study was conducted between August and October 2024, involving a total of 25 experts selected for the Delphi method expert consultation. The experts' ages ranged from 30 to 75 years old, with an average age of (45.17 ± 11.83) years. The majority held doctoral degrees, accounting for 64%. Professional titles were primarily intermediate-level, with 28% holding senior-level titles and 12% holding associate senior-level titles. The average years of work experience was (17.52 ± 7.83) years. The majority of experts are currently engaged in research (68%), teaching (56%), and trade (52%) activities. Their primary fields of expertise include education (76%), foreign languages (92%), and economics (68%). Detailed basic information about the experts is shown in Table 2.

Table 2: Detailed basic information of the expert

Basic information of experts	Classification	Number of people	Proportion
Age	30-39	8	32%
	40-49	10	40%
	50 to 59	6	24%
	Over 60	3	12%
Educational background	Master's degree	9	36%
	Doctor	16	64%
Professional and technical title	Intermediate	15	60%
	Associate senior	7	28%
	Senior senior	3	12%
Years of working experience	Less than 10 years	7	28%
	10-20	13	52%
	20-25	3	12%
	Over 25	2	8%
Currently engaged in work	Scientific research	17	68%
	Teaching	14	56%
	Trade	13	52%
	Information technology	5	20%
	Administrative management	4	16%
The professional field engaged in	Pedagogy	19	76%
	Foreign Language Studies	23	92%
	Sociology	11	44%
	Psychology	9	36%
	Educational Technology	15	60%
	Economics	17	68%

III. A. 2) Expert Authority

According to the self-reported survey forms completed by the experts, the expert familiarity coefficient Cs was calculated to be 0.76, the judgment basis coefficient Ca was 0.89, and the expert authority coefficient Cr was (Cs + Ca)/2 = 0.825, which is greater than 0.7. Therefore, the consultation results are reliable. The distribution of experts' familiarity with the indicators is shown in Table 3.

Table 3: The distribution of experts' familiarity with the indicators

Index		Coefficient
Degree of judgment (Ca)	Practical experience	0.46
	Theoretical analysis	0.24
	Consult relevant literature or materials	0.13
	Subjective intuition	0.06
	Total	0.89
Familiarity (Cs)		0.76
Expert authority coefficient (Cr)		0.825

III. A. 3) Degree of coordination of opinions

In the first round of expert consultation, the Kendall's W result was 0.154. A significance test was conducted, yielding P = 0.000 < 0.001. In the second round of consultations, Kendall's W was 0.170, with a significance test P = 0.000 < 0.001. Although the Kendall's W value was relatively low, the significance test P < 0.001 indicated that the difference was statistically significant, suggesting that expert scores were consistent and the results were reliable. The distribution of experts' familiarity with the indicators is shown in Table 4.

Table 4: The distribution of experts' familiarity with the indicators

	Number of indicators	Coordination coefficient	χ^2	P
The first round	17	0.154	273.321	0.000
The second round	16	0.170	165.039	0.000

III. A. 4) Concentration of expert opinion

The mean values of the indicators not only reflect the degree of consensus among experts but also indicate the importance of the indicators. In the first round of consultations, except for indicator C17 "Curiosity," all mean values were greater than 4, and no indicator had a coefficient of variation greater than 0.25.

In the second round of expert consultation results, after removing the tertiary indicator C17, the range of mean values for all indicators was 4.21–5.00, and the range of coefficient of variation values was 0.00–0.17. All mean values were greater than 4, and no coefficient of variation exceeded 0.25, indicating that the importance of each indicator was well-defined and expert opinions were highly concentrated. The results of the second round of expert consultation on the evaluation indicator system are presented in Table 5.

Table 5: Evaluation index system indicators expert consultation results

Index	Degree of importance		Coefficient of variation
	M	SD	
A1	4.94	0.29	0.07
A2	4.80	0.55	0.02
B1	4.94	0.67	0.08
B2	4.81	0.56	0.06
B3	4.90	0.45	0.06
B4	4.96	0.47	0.07
B5	4.81	0.30	0.13
B6	4.94	0.59	0.07
B7	4.58	0.33	0.08
C1	4.79	0.20	0.00
C2	4.80	0.30	0.00
C3	4.92	0.66	0.12
C4	4.52	0.25	0.04
C5	4.51	0.42	0.07
C6	4.33	0.44	0.06
C7	4.59	0.25	0.07
C8	4.22	0.45	0.11
C9	4.21	0.42	0.03
C10	4.33	0.12	0.15
C11	4.89	0.66	0.01
C12	4.46	0.43	0.02
C13	4.73	0.44	0.07
C14	4.69	0.53	0.00
C15	4.74	0.26	0.10
C16	4.39	0.35	0.17

III. B. Weight Determination

III. B. 1) Judging matrix consistency test

After constructing the judgment matrix, the consistency of each judgment matrix is tested using the yaahp software to assess whether there are any contradictions in the expert feedback data collected. Typically, it is challenging to ensure that all judgment matrices provided by experts meet the consistency requirements. If the consistency ratio (CR) exceeds 0.1, the judgment matrix is deemed to have failed the consistency test. In such cases, the inconsistent judgment matrices are automatically corrected using the yaahp software. Due to the large volume of data, this example focuses on the inconsistent consistency test results of one expert's judgment matrix. By applying the "minimum change" algorithm for automatic correction, the consistency requirements can be met. The consistency test results for the judgment matrices of various levels of indicators for a certain expert are shown in Table 6. After correction, the consistency ratio (CR) values are all less than 0.1, indicating that they have passed the consistency test.

Table 6: Consistency test of the judgment matrix of various levels of indicators

Judgment matrix	Maximum characteristic root $\lambda_{\max}$	Consistency index RI	Consistency ratio		Consistency check
			Before modification	After modification	
A1	3.454	1.12	0.1372	0.0959	<0.1
A2	3.393	0.00	0.1209	0.0975	<0.1
B1	3.783	0.00	0.1396	0.0969	<0.1
B2	4.226	0.00	0.1288	0.0951	<0.1
B3	4.148	0.00	0.1329	0.0956	<0.1
B4	4.465	0.00	0.1015	0.0969	<0.1
B5	4.149	0.00	0.1363	0.0980	<0.1
B6	4.469	0.90	0.1267	0.0962	<0.1
B7	4.263	0.00	0.1168	0.0956	<0.1

III. B. 2) Weight calculation results

This study employs two calculation methods for “group decision-making”: the arithmetic mean based on the coefficient of variation and the average weight based on expert opinions. After the data results are exported, the weights are sorted hierarchically in order.

Based on the hierarchical single-level sorting, the combined weights were calculated using the formula (where W represents the total weight of the indicators, Wi represents the single-level weight of the upper-level indicators, and Wij represents the single-level weight of the indicators). This means that the weights of the second-level indicators were multiplied by the corresponding weights of the first-level indicators, and the weights of the third-level indicators were multiplied by the corresponding weights of the second-level indicators, thereby calculating the combined weights of each indicator. This calculation method more accurately reflects the interrelationships between indicators, providing a more scientific and effective basis for evaluation. The results of the weight calculations for indicators at all levels are shown in Table 7.

Table 7: Weight distribution of students' critical thinking ability indicators

Primary indicator	Weight	Secondary indicator	Individual weight	Total weight	Tertiary indicator	Individual weight	Total weight
A1	0.672	B1	0.232	0.156	C1	0.542	0.085
					C2	0.458	0.071
		B2	0.229	0.154	C3	0.608	0.094
					C4	0.392	0.060
		B3	0.196	0.132	C5	0.472	0.062
					C6	0.528	0.070
		B4	0.150	0.101	C7	0.526	0.053
					C8	0.474	0.048
		B5	0.192	0.129	C9	0.427	0.055
					C10	0.573	0.074
A2	0.328	B6	0.753	0.247	C11	0.315	0.078
					C12	0.233	0.058
					C13	0.228	0.056
					C14	0.224	0.055
		B7	0.247	0.081	C15	0.677	0.055
					C16	0.323	0.026

Table 7 presents the final weight distribution results of the evaluation index system for students' critical thinking abilities after adjustment using the Delphi method and calculation using the Analytic Hierarchy Process (AHP). Among these, the weight of critical thinking skills (A1) (0.672) is significantly higher than that of critical thinking disposition (A2) (0.328), indicating that in this evaluation system, specific cognitive skills are considered more important than thinking qualities and emotional traits in measuring critical thinking ability. Within the skill dimension (A1), among the five secondary skill indicators, “questioning skills” (B1 weight 0.232 / total weight 0.156) and “analytical skills” (B2 weight 0.229 / total weight 0.154) have the highest weights and are very close, highlighting the central role of posing questions and analyzing from multiple angles. Next are “reasoning skills” (B3 total weight 0.132) and “evaluation skills” (B5 total weight 0.129), while “judgment skills” (B4 total weight 0.101) are relatively lower. At the tertiary indicator level, “Establishing Standards and Making Comparisons” (C1 total weight 0.085) is the most important specific ability under B1, while “Skills for Multi-Angle Analysis” (C3 total weight 0.094) is the most important ability under B2. In the “Tendency Dimension” (A2), the weight of “Thinking Quality” (B6 weight 0.753 / total weight 0.247) is significantly higher than that of “Emotional Traits” (B7 weight 0.247 / total weight 0.081), indicating that experts believe the characteristics of thinking itself better represent the tendency toward critical thinking than emotional attitudes. Among the tertiary indicators under B6, “thinking proactivity” (C11 total weight 0.078) is assigned the highest weight. Under B7, the weight of “self-confidence” (C15 total weight 0.055) is significantly higher than that of “boldness and courage” (C16 total weight 0.026).

The top-weighted tertiary indicators are “Skills in Analyzing from Multiple Perspectives” (C3: 0.094), “Skills in Establishing Standards and Making Comparisons” (C1: 0.085), “Skills in reasoning about questionable content based on assumptions” (C6: 0.070), and “Skills in assessing the potential risks and benefits of decisions” (C10: 0.074). These indicators should be given particular attention when comprehensively evaluating students' critical thinking abilities.

IV. GA-BP neural network evaluation model

The weighting of the student critical thinking ability evaluation index system constructed through the aforementioned coefficient of variation method (CVM) provides important basic data for quantifying the actual effectiveness of integrating ideological and political elements into EFL classrooms. To achieve dynamic modeling, precise prediction, and intelligent optimization of teaching strategies for students' critical thinking abilities, this study further introduced neural network technology with strong nonlinear fitting and learning capabilities, and specifically enhanced it with genetic algorithms to construct a GA-BP neural network prediction model.

IV. A. BP Neural Network Structure

A BP neural network is a multi-layer feedforward network consisting of an input layer, at least one hidden layer, and an output layer. The structure of a BP neural network is composed of multiple layers of neural nodes and the connections between them, where each neuron is connected to all neurons in the previous layer.

The algorithm process primarily includes two stages: forward propagation and backward propagation. These two stages alternate, continuously adjusting connection weights to minimize the error between the network output and the actual output, thereby achieving learning and pattern recognition of the input data. Specifically:

(1) Input layer: The input layer receives external data, with each input neuron node corresponding to a feature of the input data. For example, if we are training an image classification model, each input node can represent a pixel value or feature in the image.

(2) Hidden Layer: The hidden layer is located between the input layer and the output layer and serves as an intermediate layer in the network. Its role is to extract and abstract features from the input data, mapping the input data to a higher-dimensional feature space. The hidden layer can contain one or more neural nodes. Each hidden layer neural node receives the output from the previous layer's neural nodes, performs a weighted sum using connection weights, and then applies a nonlinear transformation through an activation function to generate the hidden layer's output.

Each hidden layer neuron receives the output from the input layer or the previous hidden layer as the input signal x_i . These input signals can be feature values of the raw data or the output of neurons in the previous layer. Each signal is transmitted through a connection with a weight w and a bias value b . The neuron sums these signals to obtain a total input value y , then compares the total input value with the neuron's threshold (simulating the threshold potential), and finally processes it through an “activation function” to obtain the final output (simulating the activation of the cell). This output is then passed on as input to subsequent neurons layer by layer.

The introduction of activation functions in BP neural networks aims to enhance the network's nonlinear fitting capability, address the vanishing gradient problem, and strengthen the network's sparsity. By introducing nonlinear mappings, activation functions enable neural networks to better adapt to and learn complex nonlinear relationships, thereby improving the model's expressive power and generalization ability, making it effectively applicable in fields such as pattern recognition and data classification.

Common activation functions θ include:

S -type function:

$$f(x)=\frac{1}{1+e^{x}} \tag{1}$$

This function has a value range of $(0,1)$, is monotonically continuous, and is differentiable everywhere. It is generally used for hidden layers and binary classification output layers.

Tanh function:

$$f(x)=\frac{e^{x}-e^{-x}}{e^{x}+e^{x}} \tag{2}$$

This function has a value range of $(-1,1)$, is monotonically continuous, and is differentiable everywhere. It is generally used for hidden layers and binary classification output layers.

Relu function:

$$f(x)=\max(0,x) \tag{3}$$

The output of the derivative is still non-zero and asymmetric, and may result in dw being either consistently positive or consistently negative, thereby affecting training speed.

(3) Output layer: The output layer receives the output from the hidden layer and generates the final output result of the network. For example, in a classification task, each neuron node in the output layer can represent a category and output the probability or confidence of that category. The activation function of the output layer is typically determined based on the specific task. For example, the Sigmoid function can be used in a binary classification task, while the Softmax function can be used in a multi-classification task.

IV. B. Computational Process of Genetic Algorithms

The computational process of genetic algorithms begins with the generation of an initial population. Through a series of operations, including decoding, determining the fitness function, selection, crossover, and mutation, the process undergoes continuous optimization to ultimately obtain the most optimal individuals. The computational flow of genetic algorithms is shown in Figure 1.

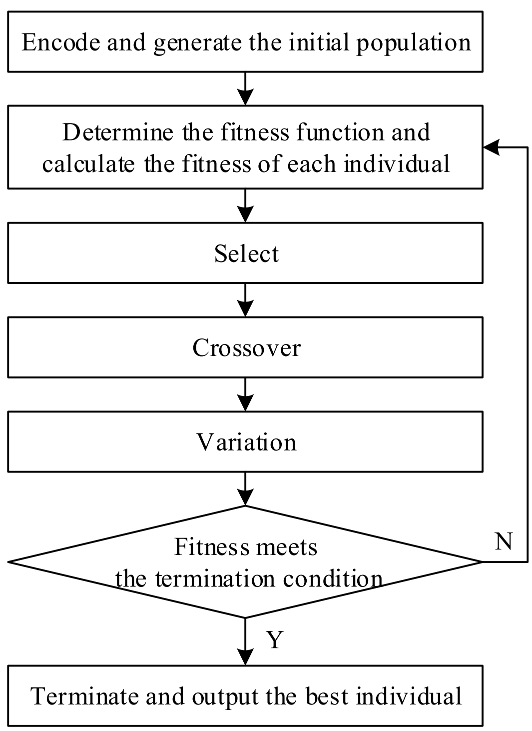

Figure 1: Genetic algorithm calculation process

IV. B. 1) Generating the initial population

Before starting the genetic algorithm calculation, it is necessary to first determine an initial population, which serves as the first generation at the start of evolution. The size of the initial population is critically important. A population that is too small may cause the algorithm to fail, as the search is prone to getting stuck in local optima. Conversely, a population that is too large will increase the computational load of the algorithm, significantly reducing search efficiency. Therefore, the size of the initial population should be determined based on the specific problem being addressed, avoiding both excessive and insufficient sizes. Specifically, a balance must be struck between search efficiency and computational load to achieve optimal computational results.

IV. B. 2) Encoding

Coding is a crucial foundation for the smooth operation of genetic algorithms. It transforms biologically complex traits into computable genetic data through specific methods. Genomes and chromosomes are composed of multiple genes. During the computational process of genetic algorithms, the algorithm does not directly handle the complex traits of the target problem but instead performs operations such as crossover and mutation on the genetic data to generate feasible solutions. Real-number encoding is currently the most commonly used encoding method. Real-number encoding refers to connecting the weights and thresholds in a BP neural network into an array in a specific order to generate the chromosomes of each individual in the genetic algorithm. To ensure the computational efficiency and accuracy of the genetic algorithm, the design of the encoding must consider the characteristics and requirements of the actual problem to obtain the optimal solution. The BP neural network structure selected in this paper consists of three layers: the input layer, the hidden layer, and the output layer, with the number of neural nodes being n, a, and b, respectively. The encoding length of the chromosome R for each individual in the population is:

$$R = n \times a + a \times b + a + b \tag{4}$$

IV. B. 3) Fitness Function

In nature, the degree of adaptation of organisms determines their survival or elimination. In genetic algorithms, it is necessary to select superior individuals for crossover and mutation operations. To assess the quality of an individual, a fitness function is used to describe the difference between the computed result and the desired result. Therefore, the design of the fitness function significantly influences the algorithm's ability to find the optimal solution. In GA-BP neural networks, fitness can be viewed as the sum of squared errors between the network's output values and the desired output values $E(i)$. The smaller the error, the higher the fitness. Therefore, the fitness function can be defined as:

$$H(i) = \frac{1}{E(i)} = \frac{1}{\sum_{k=1}^{n}(\hat{y} - y_k)^2} \tag{5}$$

IV. B. 4) Selection

In genetic algorithms, selection refers to the process of selecting individuals with stronger fitness from the population to serve as parents for self-replication. The stronger an individual's fitness, the higher the probability of being selected as a parent, thereby passing on its genes to the next generation. The roulette wheel method is typically used for selection operations. This method represents the proportion of each individual's fitness relative to the total fitness of the population as a corresponding sector on a circular disk. By using the roulette wheel method for selection, the probability of fitness-strong individuals being selected as parents is increased, thereby improving the efficiency of the algorithm.

The formula is as follows:

$$P_i = \frac{H_i}{\sum_{i=1}^{M} H_i} \tag{6}$$

In the formula, P_i represents the probability that individual i is selected.

IV. B. 5) Cross

In genetic algorithms, crossover is a primary operation used to generate new individuals. It enhances the ability for global search by exchanging some genes between the chromosomes of two individuals to produce new chromosomes. Common crossover methods include single-point crossover and multi-point crossover. The principles behind single-point crossover and multi-point crossover are similar; the following provides a brief introduction to single-point crossover.

Single-point crossover involves randomly cutting two chromosomes at a single point, recombining the A segment before the cut with the B segment after the cut to form a new chromosome A_1, and recombining the A segment after the cut with the B segment before the cut to form another new chromosome B_1. The process is illustrated in Figure 2.

$$\begin{array}{l|l} \mathrm{A:101} & \mathrm{001} \\ \mathrm{B:110} & \mathrm{010} \end{array} \xrightarrow{\text{Cross}} \begin{array}{l} \mathrm{A_1:101010} \\ \mathrm{B_1:110001} \end{array}$$

Figure 2: Single point intersection

The k th chromosome c_k and the l th chromosome c_l swap chromosomes at the crossover point j, generating new chromosomes c'_{kj} and c'_{lj}, whose calculation formula is:

$$\begin{cases} c'_{kj} = c_{kj}(1-d) + c_{lj}d \\ c'_{lj} = c_{lj}(1-d) + c_{kj}d \end{cases} \tag{7}$$

In the formula, d is a random number between $(0,1)$.

IV. B. 6) Variation

Mutation is the process of mutating selected individuals according to a specific probability to form new individuals. Mutation selects the y th gene of the x th chromosome according to a random probability r for mutation, and obtains the mutated chromosome. The expression is:

$$c'_{xy} = \begin{cases} c_{xy} + (c_{xy} - c_{\max}) f(t) & r > 0.5 \\ c_{xy} + (c_{\min} - c_{xy}) f(t) & r \le 0.5 \end{cases} \tag{8}$$

In the equation, $c_{\max}$ represents the upper bound of gene c_{xy}, $c_{\min}$ represents the lower bound of gene c_{xy}, $f(t) = r_1(1 - t / G_{\max})$ t is the current iteration count, $G_{\max}$ is the maximum number of iterations, r_1 is a random number, and r is a random number between $(0,1)$.

IV. C. Building a GA-BP neural network model

The BP neural network model consists of three structures: the input layer, the hidden layer, and the output layer. The method for determining the number of neurons in the input layer and output layer is as follows: since the three-level indicators for evaluating students' critical thinking abilities obtained using principal component analysis (PCA) total 16, the number of neurons in the input layer of the BP neural network model is 16, i.e., the number of input nodes; The results of teaching quality evaluation can be represented by a single numerical value, so a single output neuron is sufficient to fully describe the teaching quality evaluation results, with the output layer having 1 node. The method for determining the number of nodes in the hidden layer of the BP neural network model for teaching quality evaluation is as follows: To objectively and scientifically determine the number of nodes in the hidden layer, after multiple tests and drawing on prior research experience, the number of neurons in the hidden layer is calculated using formula (9):

$$B_{hid} = \sqrt{(B_{in} + B_{out})} + \kappa = \log_2 B_{in} \tag{9}$$

In this context, the nodes in the input layer, hidden layer, and output layer are described by B_{in}, B_{hid}, and B_{out}, respectively, with κ taking values in the range $[1,10]$.

The backpropagation (BP) neural network uses the mean squared error (MSE) as the performance evaluation metric. When the MSE of the training samples is less than or equal to 10^{-4} and the error no longer increases, the network training can be terminated. The MSE is calculated as follows:

$$E_{\mathrm{ms}} = \frac{1}{mp} \sum_{p=1}^{p} \sum_{j=1}^{m} (\hat{y}_{pj} - y_{pj})^2 \tag{10}$$

In this context, the output layer nodes are denoted by m, the total number of training samples is denoted by p, and the expected output and actual output of the BP neural network are described as $\hat{y}_{pj}$ and y_{pj}, respectively.

The training of the BP neural network is implemented using the adaptive gradient descent method, employing the Trainbp training function. The activation functions for the input layer, hidden layer, and output layer are respectively the Tansig function, the tangent S type transfer function, and the Purelin function. The input and output values are randomly selected numerical values, with the initial weights and thresholds set to their default values. The initial weight settings for the BP neural network are generally randomly selected within a certain range. To enhance the scientific nature of the network testing, the initial weights of the BP neural network are optimized using a genetic algorithm, and the initial weight selection range is set to $[0,1]$.

V. Neural network-based model for evaluating students' critical thinking skills

By constructing and training a GA-BP neural network model, this study provides a technical foundation for dynamic assessment and prediction. Furthermore, the model is applied to real-world scenarios, combining empirical data to conduct an in-depth analysis of the actual promotional effects of integrating ideological and political elements into EFL classrooms on students' critical thinking abilities, as well as group differences.

V. A. MATLAB implementation of BP neural network structure

V. A. 1) Training Process

Based on the basic structure of a BP neural network, a three-layer network model was established to assess students' critical thinking abilities. The network structure is a multi-layer feedforward neural network, utilizing neural network algorithms and parameters trained using MATLAB. In the algorithm, the Rand function was used to randomly partition the data, and the Levenberg-Marquardt optimization algorithm was employed to optimize and train the model.

During the computation process, to prevent overfitting, the value of the objective function (MSE) was 0.000990 (less than the pre-set 0.001), and the error descent gradient was 0.0623. From the BP neural network training parameter diagram, the model underwent 5 iterations, and the validation set error no longer decreased. To prevent overfitting, based on the early stop principle, the model training was stopped. The model gradient value was 0.062299, and the model tended toward optimization during iteration. The predicted output and expected output began to converge after multiple iterations.

V. A. 2) Analysis of network training results

The training of the BP neural network and the quality of the network's testing directly determine its fitting ability and generalization ability, as well as the overall quality of the network. Using data from the test sample set, the neural network constructed from the training set is tested. After multiple runs of MATLAB experiments, a set of simulation models with good fitting performance is selected as the evaluation results for mathematical modeling capability. MATLAB is used to analyze the errors during the mathematical modeling capability testing process. After training, the predicted values of the test samples are very close to the expected values and eventually converge. After five iterations, the optimal performance of 0.000682635 is achieved.

Figures 3-6 show the fitting analysis in the training set, validation set, test set, and overall training process, respectively. It can be seen that the model fitting coefficients are all around 0.999. Except for a few outliers, the training sample points are almost all on or near the fitting line, meaning that the predicted values are very close to the actual values. Using MATLAB calculations, the mean squared error was determined to be 0.0053178, which is less than the set target of 0.01, meeting the error requirement. This indicates that the BP neural network training results are highly satisfactory. Based on the evaluation data from the 10 test samples obtained from this network, the error between the predicted values generated by the BP neural network and the initial expected values was calculated. The errors between the test set and the expected values fluctuate around 0, with the maximum error being 0.1283 and the maximum error percentage being 1.17%. The small error indicates that the BP neural network has effectively absorbed the expert knowledge and experience from the AHP model, resulting in good test performance.

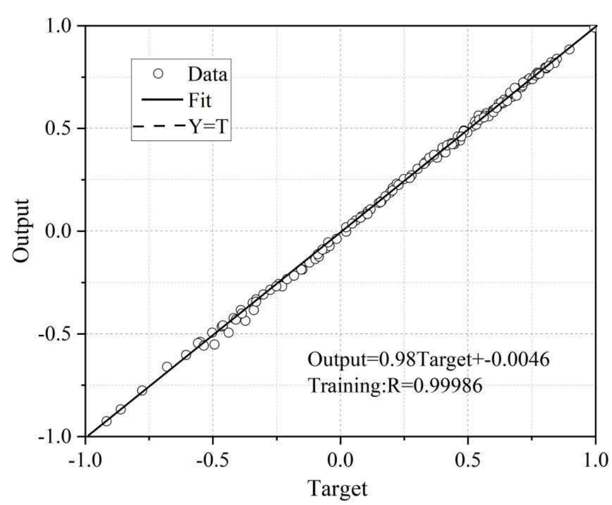

Figure 3: Analysis of fitting degree during training process on the training set

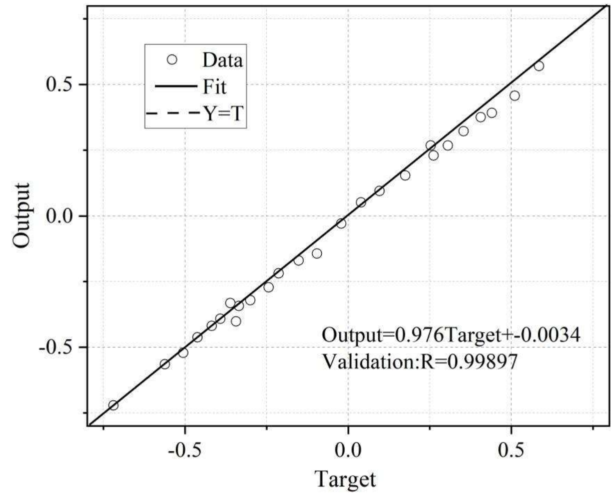

Figure 4: Analysis of the fitting degree of the training process on the validation set

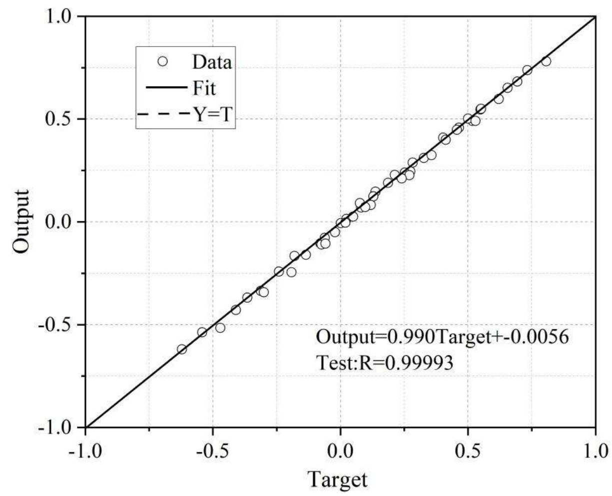

Figure 5: Analysis of the fitting degree of the training process on the test set

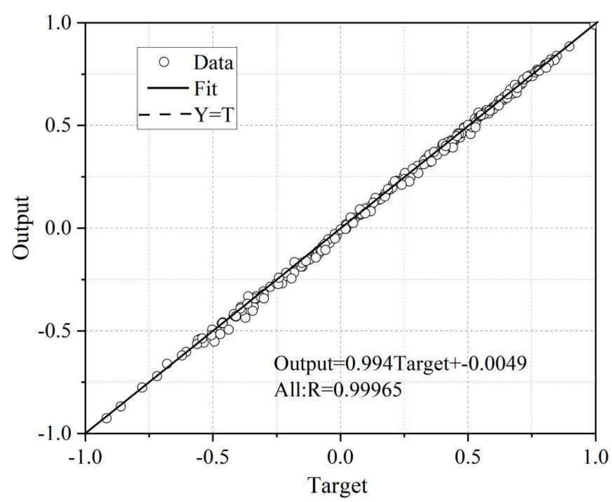

Figure 6: Analysis of the fitting degree of the training process of all

V. B. Empirical Analysis of Students' Critical Thinking Skills in EFL Classrooms Incorporating Ideological and Political Education

Based on the overall predictive assessment of critical thinking skills using the GA-BP model, this section focuses on the analysis of empirical data to reveal in greater detail the actual effects of integrating ideological and political education into the classroom among different student groups. First, students were stratified according to their academic performance, and their specific differences in critical thinking skills were examined in detail.

V. B. 1) Comparison of critical thinking skill dimensions based on academic achievement levels

This study utilized validated critical thinking assessment questions integrated with ideological and political elements in EFL English classrooms. The assessment targeted students from a certain university, with the collected data input into SPSS 26.0 software for analysis. The aim was to explore the development status and existing issues of critical thinking among university students, thereby providing a basis for formulating targeted educational strategies in the future.

A total of 600 students from various majors of a certain university in the class of 2024 were selected. 600 survey questionnaires were distributed, and 574 were returned, with a response rate of 95.67%. The seven indicators for evaluating students' critical thinking abilities were scored on a 10-point scale, and students were categorized into three levels based on their academic performance: top performers, average performers, and underperformers. The average scores for each dimension of critical thinking skills among the 574 students are shown in Table 8. The average scores for each element are also listed in a bar chart as shown in Figure 7.

Table 8: Statistics of the various dimensions of students' critical thinking skills

	Top students			Regular students			Struggling students		
	Number of students	M	SD	Number of students	M	SD	Number of students	M	SD
B1	188	9.54	0.35	311	6.31	2.3	75	4.35	2.31
B2	156	9.63	0.21	341	6.70	2.2	77	3.56	1.67
B3	204	9.87	0.08	288	7.53	1.1	82	4.37	2.11
B4	165	9.63	0.31	295	7.49	0.96	114	3.58	2.85
B5	243	9.10	0.65	308	6.06	1.11	23	4.09	2.84
B6	174	9.25	0.59	297	7.54	2.04	103	5.42	2.91
B7	200	9.42	0.57	318	8.15	1.41	56	3.71	1.22

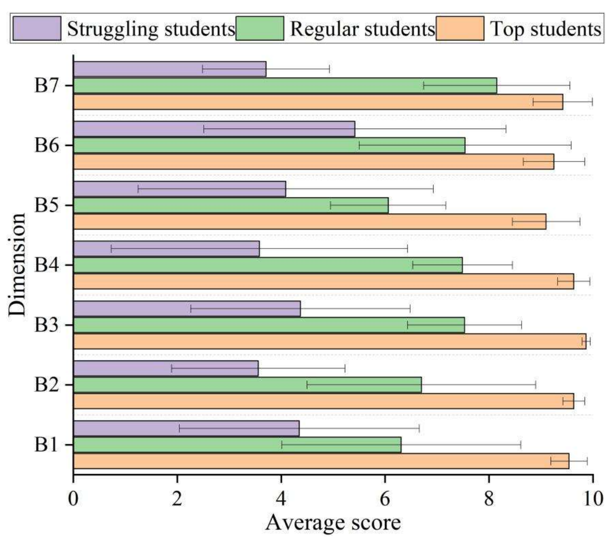

Figure 7: The scores of each dimension of critical thinking skills at different levels

Among the 574 valid samples, there were 156–243 high-achieving students, 288–341 average-achieving students, and 23–114 low-achieving students. The proportion of average students was the highest (50.5%–59.4%), while the proportion of struggling students was the lowest (4.0%–19.9%). Among these, the average scores of top-performing students were significantly higher (9.10–9.87), average students were in the middle (6.06–8.15), and struggling students were significantly lower (3.56–5.42).

High-achieving students scored ≥9.10 on average across all dimensions, approaching the maximum score. They scored highest on B3 (reasoning skills) (9.87 ± 0.08), with an extremely small standard deviation, indicating high consistency in group performance. They scored relatively lowest on B5 (evaluation skills) (9.10 ± 0.65), but still remained at a high level. The standard deviation across all dimensions ranged from 0.08 to 0.65 (far lower than other groups), reflecting balanced and stable abilities.

The average scores of students at the intermediate level varied significantly (6.06–8.15), showing clear differentiation. They performed best in B7 (emotional traits) (8.15 ± 1.41), approaching the level of high-achieving students. B5 (evaluation skills) was the weakest (6.06 ± 1.11), with the largest gap from top-performing students (3.04 points). The standard deviation ranged from 0.96 to 2.30 (e.g., B1 had a standard deviation of 2.30), indicating significant individual differences within the group.

The scores of struggling students were below 5.42 in all dimensions, with B2 (analytical skills) being the lowest (3.56 ± 1.67), less than 40% of the top students' scores. B6 (thinking quality) was relatively the highest (5.42 ± 2.91), but still showed a significant gap compared to average students. The standard deviation ranged from 1.22 to 2.91 (e.g., B4 reached 2.85), reflecting extremely uneven ability distribution within the group.

High-achieving students significantly outperformed in all dimensions (average score > 9.10), while struggling students lagged behind across the board (average score < 5.42), highlighting the strong correlation between critical thinking and academic performance. Regarding B5 (evaluation skills), both average students (6.06) and struggling students (4.09) scored at the bottom, indicating a common weakness across groups. Struggling students scored only 3.56 in B2 (analytical skills), the lowest value across all dimensions, necessitating targeted reinforcement.

V. B. 2) Multiple linear regression analysis

The aforementioned hierarchical comparison revealed significant differences in critical thinking skills among students of varying academic levels. To further explore the key factors influencing critical thinking abilities, particularly the role of variables related to the integration of ideological and political elements into classroom strategies, we next employed multiple linear regression analysis to quantitatively examine the promotional effects of variables such as grade level, major, English proficiency, frequency and depth of classroom implementation, interaction, and task design on students' critical thinking abilities.

To investigate the promotional impact of integrating ideological and political elements into EFL classrooms on students' critical thinking abilities, we selected grade level (whether graduates), major (humanities/science), students' English language proficiency, the depth and quality of ideological and political element integration, the number of classroom sessions per week, the frequency of teacher-student interaction in the classroom, and the number of critical thinking-oriented teaching task designs as factors for multivariate linear regression analysis. The results of the multivariate linear stepwise regression analysis of students' critical thinking abilities are shown in Table 9.

Table 9: The multiple regression analysis of students' critical thinking abilities

Item	β	95%CI	P
Constant	99.699	96.125-104.738	0.000
Grade (whether it is a graduate)	2.601	0.327-5.384	0.001
Major (Liberal Arts/Science)	3.549	1.364-5.271	0.000
Student English language proficiency	4.403	2.091-7.052	0.000
Depth and quality of ideological and political elements integration	3.350	1.314-5.137	0.000
Number of classes conducted per week	3.981	1.527-5.613	0.000
Number of times of teacher-student interaction in class	2.501	0.839-4.608	0.005
Number of times of teaching tasks designed with a critical thinking orientation	3.699	1.482-5.125	0.000

The regression results for the seven single factors show that all variables included in the model are significantly positively correlated with students' critical thinking abilities (all $P < 0.01$). The standardized regression coefficients (β) are all greater than 0, indicating that these factors have a positive promotional effect on the improvement of students' critical thinking abilities. The effects, ranked from largest to smallest, are as follows: students' English language proficiency ($\beta = 4.403$), the number of classroom sessions conducted per week ($\beta = 3.981$), the number of critical thinking-oriented teaching tasks designed ($\beta = 3.699$), major (humanities/sciences) ($\beta = 3.549$), the depth and quality of ideological and political elements integrated into teaching ($\beta = 3.350$), grade level (whether a graduate) ($\beta = 2.601$), and frequency of teacher-student interaction in class ($\beta = 2.501$). The lower limits of the 95% confidence intervals (95% CI) for all independent variables are greater than 0. The CI for English language proficiency is 2.091–7.052, and the CI for the depth of integration of ideological and political education is 1.314–5.137. These findings further confirm that these factors have a statistically significant positive effect on the improvement of critical thinking skills.

VI. Conclusion

This study systematically quantified the promotional effect of integrating English ideological and political elements into EFL classrooms on students' critical thinking abilities by integrating the Coefficient of Variation Method (CVM) with genetic algorithm optimization of the BP neural network (GA-BP). The main conclusions are as follows:

(1) The critical thinking ability evaluation system modified using the Delphi method includes 2 primary indicators (skills/tendencies), 7 secondary indicators, and 16 tertiary indicators (after removing C17 “curiosity”), with an expert authority coefficient Cr = 0.825.

(2) The coefficient of variation method shows that critical thinking skills (weight 0.672) are significantly more important than thinking tendencies (weight 0.328), with the core competencies being “multi-angle analysis (C3, total weight 0.094)” and “determining standards and comparisons (C1, weight 0.085).”

(3) After optimization via genetic algorithms, the structural neural network model for students' critical thinking abilities achieved a mean squared error (MSE) of 0.000682 on the test set, with a coefficient of determination of 0.999 and a maximum prediction error of only 1.17% (converged after 5 iterations), confirming the model's ability to accurately and dynamically assess students' skill development.

(4) The average scores of top-performing students ranged from 9.10 to 9.87 (standard deviation 0.08–0.65), significantly leading the pack; the average scores of struggling students were only 3.56–5.42, with the lowest score in “Analytical Skills (B2)” (3.56 ± 1.67); The average score for evaluation skills (B5) among average students was the lowest (6.06 ± 1.11), indicating a common weakness across groups.

(5) Multiple regression analysis revealed that English language proficiency (β = 4.403, $P < 0.001$) and the frequency of classroom implementation (β = 3.981, $P < 0.001$) had the strongest influence; the depth of integration of ideological and political elements (β=3.350, $P<0.001$) and critical task design (β=3.699, $P<0.001$) significantly promote ability improvement; liberal arts students have a greater advantage than science students (professional difference β=3.549, $P<0.001$).

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References

[1] Wang, G. (2025). The Integration Strategy of Ideological and Political Education for College Students Based on Course-based Ideological and Political Education. Educational Innovation Research, 3(2), 18-23.

[2] Ling, Z. (2023). Principles and Improvement Path of Ideological and Political Education in College English Curriculum. Frontiers in Educational Research, 6(25).

[3] Si, L. (2024). Exploration of the Course Construction of" Public English for Postgraduate" Under the Course-based Ideological and Political Education Guidance in the Digital and Intelligent Era. The Educational Review, USA, 8(12), 1496-1501.

[4] Yang, S. (2024). The Integration Path of Continuing Writing Mode and Ideological and Political Education in College English Writing Teaching. International Journal of New Developments in Education, 6(10).

[5] Manalu, D. B., & Marpaung, T. I. (2018). Student Teachers’ Ways To Integrate Character Values In EFL Classroom. J. Humanit. Soc. Sci, 23(7), 37-42.

[6] Liu, F., Wang, X., & Izadpanah, S. (2023). The comparison of the efficiency of the lecture method and flipped classroom instruction method on EFL students’ academic passion and responsibility. Sage Open, 13(2), 21582440231174355.

[7] Feng, W. D. (2019). Infusing moral education into English language teaching: an ontogenetic analysis of social values in EFL textbooks in Hong Kong. Discourse: Studies in the Cultural Politics of Education, 40(4), 458-473.

[8] Fu, H., & Wang, J. (2021). Cultivation of critical thinking skills in college English writing under blended learning model. Creative Education, 12(7), 1485-1493.

[9] Iman, J. N. (2017). Debate Instruction in EFL Classroom: Impacts on the Critical Thinking and Speaking Skill. International Journal of Instruction, 10(4), 87-108.

[10] Rahmawati, A. (2018). EFL students' critical thinking in speaking activities (a descriptive study at English conversation club (ECC) in SMAN 1 Maja). Journal of English Language Learning, 2(2), 318851.

[11] Song, W. (2019). Study on the influence of teachers' questioning in high school English reading class on students' critical thinking. Theory and Practice in Language Studies, 9(4), 424-428.

[12] Wu, Z. (2024). A Study on the Cultivation Mode of Students’ Critical Thinking Ability Based on College English Curriculum. Journal of Higher Education Teaching (2).

[13] Du, Y. (2023). Research on Exploring and Integrating Ideological-Political Elements in College Public English Textbooks. International Education Studies, 16(1), 104-109.

[14] Novák, L., & Novák, D. (2021). Estimation of coefficient of variation for structural analysis: The correlation interval approach. Structural Safety, 92, 102101.

[15] Chankham, W., Niwitpong, S. A., & Niwitpong, S. (2022). Measurement of dispersion of PM 2.5 in Thailand using confidence intervals for the coefficient of variation of an inverse Gaussian distribution. PeerJ, 10, e12988.

[16] Siregar, S. P., & Wanto, A. (2017). Analysis of artificial neural network accuracy using backpropagation algorithm in predicting process (forecasting). IJISTECH (International Journal of Information System and Technology), 1(1), 34-42.
[17] Jeong, T. (2020). Deep neural network algorithm feedback model with behavioral intelligence and forecast accuracy. Symmetry, 12(9), 1465.
[18] Wang, L., You, Z. H., Chen, X., Xia, S. X., Liu, F., Yan, X., ... & Song, K. J. (2018). A computational-based method for predicting drug–target interactions by using stacked autoencoder deep neural network. Journal of Computational Biology, 25(3), 361-373.