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# Method of Cultivating College Students' Independent Learning Ability Based on Integration of Multiple Algorithm

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## Abstract

INTRODUCTION: The research on the multi-mode fusion of college students' independent learning ability cultivation method is conducive to college students' change of learning mode and learning thinking, improvement of the utilization rate of educational resources, and the development of the academic environment as well as the reform of the educational concept.
OBJECTIVES: Aiming at the problems of college students' current independent learning mode, such as the need for more in-depth research and the single study means.
METHODS: A method for cultivating college students' autonomous learning ability through the integration of intelligent optimization algorithms and multiple modes has been proposed. Firstly, the practices of analyzing the current college students' autonomous learning mode and multiple learning modes are analyzed; then, using the butterfly optimization algorithm, a weight optimization method for the cultivation of college students' independent learning ability based on the fusion of multiple modes is proposed; finally, the validity and robustness of the proposed method are verified through experimental analysis.
RESULTS: The results show that the proposed method has a high cultivation effect.
CONCLUSION: Solves the problem of fusion of college students' independent learning ability cultivation modes.

**Keywords**: college students' independent learning ability cultivation, multiple modes integration, blended learning model, butterfly optimization algorithm

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## 1 Introduction

With the rapid development of the network, new learning modes have emerged and developed in the education field industry, forming a learning environment in which multiple learning modes are integrated [1]. The traditional learning methods are constantly receiving the impact of networkization, which cannot meet the needs of people's learning, thus leading to a change in the mode of learning. College students' independent learning ability as a new generation of college students to adapt to the employment environment and the competitive environment necessary knowledge, with the change of the learning mode, the required training strategy has also changed [2]. Internet technology supported by computer and information technology provides a convenient, fast, and fair channel for college students' independent learning, which solves the limitations of place, time, and way of traditional learning mode [3]. The research on the multi-mode integration of college students' independent learning ability cultivation method is conducive to college students' change of learning mode and learning thinking, improving the utilization rate of educational resources, as well as the development of the academic environment and

the reform of the educational concept [4]. Therefore, studying teaching evaluation systems in vocational colleges and universities is an urgent and essential research topic [5].
College students' independent learning refers to individual college students setting their own learning goals and acquiring knowledge through their learning methods without the supervision of others [6]. College students' independent learning ability based on network environment mainly refers to their individual use of network mode to diversify their independent learning ability to acquire knowledge suitable for themselves and transform their independent learning ability more efficiently [7]. Currently, college students' learning modes are mainly divided into traditional, network, and blended learning modes [8]. Blended learning mode refers to the combination of two modes of on-site learning and network learning, which is not only a simple mixture of online learning and offline learning but also the integration of the learning environment and structure under the two learning modes [9]. Starting from the connotation of blended learning, literature [10] gives the definition of blended learning mode and believes that blended learning approach mobilizes students' personalized development; literature [11] summarizes different blended learning modes, including fully online mode, buffet mode, fully online mode, center mode, and assisted mode; literature [12] proposes a driving mode based on three blended learning approaches. The ambitious model is analyzed using skills, abilities, and attitudes. Literature [13] offers a blended learning model based on the Blackboard platform, which is comparatively analyzed in terms of learning effect and learning interest; Literature [14] constructs a blended learning method for vocational education based on mobile APP; Literature [15] focuses on proposing a blended learning model based on a large number of literature analyses and questionnaires. The blended learning model is based on accounting specialty. Analyzed by the above literature, there are the following deficiencies in the current approach to the cultivation of college students' autonomy: 1) there is not much literature considering the blended learning mode under the Internet, and it only stays in the theoretical analysis; 2) quantitative data do not support the qualitative analysis, and the breadth and depth of the investigation are lacking; 3) the blended learning method only gives the cultivation countermeasures, and it does not give the quantitative analysis and the integration of the methodological scheme.
In recent years, various meta-heuristic optimization algorithms have been proposed and improved by many scholars to be applied to their research areas. However, the No Free Lunch (NFL) theory [16] states that no single algorithm can be considered universal for solving all optimization problems. Thus, the approach encourages researchers to seek to develop more effective optimization algorithms to solve the problem they are studying. Aiming at the above issues of the mixed-mode college students' independent learning ability cultivation method, this paper proposes a multi-mode fusion cultivation method of college students' autonomous learning ability based on an intelligent optimization algorithm.
The main contributions of this paper are (1) analyzing three college students' independent learning modes; (2) proposing a multimodal college students' independent learning ability cultivation method by analyzing the shortcomings of the blended learning mode; (3) proposing a weight optimization method based on multimodal fusion of college students' independent learning ability cultivation by using the butterfly optimization algorithm; and (4) verifying the method of this paper through experiments that it is effective and robust.

## 2 Analysis of independent learning mode of college students

In this section, the literature analysis method is used to investigate the independent learning ability of college students and analyze the independent learning ability of college students in three modes: networked, traditional, and blended.

### 2.1 Networked Learning Model

The networked learning mode of college students is mainly based on students' independent learning, and students, as the core subjects of this mode, learn independently by cultivating their self-learning ability and using the network to interact with teachers and students. The characteristics of networked learning mode include: 1) Unidirectional teaching process. Teachers cannot observe students' concentration in time to make timely teaching adjustments, and there needs to be more feedback on the cultivation of students' self-learning ability; 2) Insufficient authenticity of learning evaluation. Since the online learning process cannot achieve real-time feedback, it is impossible to comprehensively and truly grasp the level of student's independent learning; 3) practical teaching cannot be carried out [17].
Networked learning mode lacks the atmosphere of collective learning mutual influence, students' concentration is not enough, self-control is insufficient, and attention is easily dispersed; teacher-student interaction and joint supervision among students lead to students' easy fatigue and other situations, poor feedback, and reduced learning efficiency [18].
The networked learning model can promote resource sharing and teacher growth while enhancing learning flexibility and individual attention. Students can be free from time constraints and location restrictions at any time according to their situation, targeted learning, and adaptive mastery of learning progress [19].

### 2.2 Traditional Learning Models

The traditional learning mode requires students to communicate and discuss with the teacher face-to-face at a fixed time and place [20]. The conventional learning mode has the following characteristics: 1) students need to arrange their own time by the teaching plan, time flexibility is poor; 2) learning resources are limited, limited to the teacher's lectures and teaching materials, textbooks; 3) the teaching method is relatively uniform, the students need to follow the learning by the teacher's teaching plan; 4) the interaction is strong, the interaction between the teacher and the students to achieve face-to-face, and has a supervisory role, the interaction between students Exchange to promote the competitive ability of college students to learn.

The networked learning model promotes teacher growth and student learning outcomes, can increase interactivity, and has more real-time feedback [21].

## 2.3 Blended learning model

The blended learning model is a new learning model developed by combining the online and traditional learning models. The integrated learning mode combines online and face-to-face learning modes and various advantages of network-based and face-to-face teaching modes. From the perspective of teachers' teaching, the blended learning mode can play the role of teachers' guidance, inspiration, and supervision of students; from the perspective of students, the integrated learning mode can play the role of students' main body's enthusiasm, creativity, and initiative [22]. The elemental relationship of the blended learning model is shown in Figure 1.

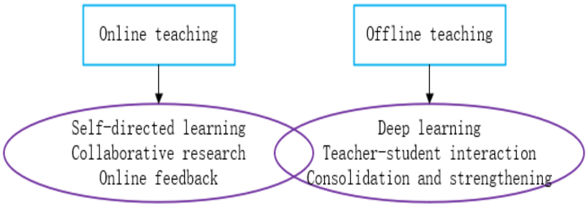


Figure 1 Relationship diagram of the elements of the blended learning model

The blended learning model combines an online model with a face-to-face offline model to acquire the skills and knowledge that people need through self-directed and supervised learning. A summary of the characteristics of the blended learning model includes: 1) Initiative. This learning mode mainly depends on students' initiative, with the ability of independent planning, independent learning, independent feedback, etc.; 2) Independence. The learning mode is through the network and does not require supervision and guidance from teachers and others; 3) Effectiveness. The learning mode can optimize their learning process, effectively improving college students' independent learning ability.

The blended learning model combines network technology with education and learning, considering the development and cultivation of students' independent learning ability and the improvement of teachers' teaching quality. In the new era, the network-based blended learning mode dramatically improves the independent learning ability of college students and efficiently develops their independent learning ability with the following advantages:

(1) Resource utilization rate

The network characteristics of the blended learning mode provide college students with maximized learning resources for independent learning, not only to improve the utilization rate of help from a quantitative point of view but also to ensure that college students can find the information resources they want, which significantly improves the efficiency of the use of resources.

(2) Learning motivation

The network-based blended learning mode entirely plays into students' independent learning ability. College students not only have a complete understanding of independent learning, realize that learning is not for parents and teachers but for self-improvement, and at the same time, combine the initiative and enthusiasm of learning according to their learning characteristics and abilities, formulate their own learning goals, improve their learning methods, and significantly improve their motivation.

(3) Teaching efficiency

Compared with the traditional learning mode, the supervision characteristics of the blended learning model of the educational model have changed. The college students use network resources to increase enthusiasm and orientation, improving autonomy, thus reducing the work pressure on teachers and prompting teachers to have more time to study to improve the efficiency of teaching methods.

# 3 Multimodal college students' independent learning mode analysis

Based on the analysis of college students' autonomous learning modes in the previous section, this subsection analyzes the deficiencies of the current blended learning modes. It proposes a multi-modal-based method for cultivating college students' independent learning abilities.

## 3.1 Deficiencies in the current blended learning model

The present composite learning mode combines the advantages of online and offline methods to improve the independent learning ability of college students. The current blended learning model still has deficiencies, as shown in Figure 2.

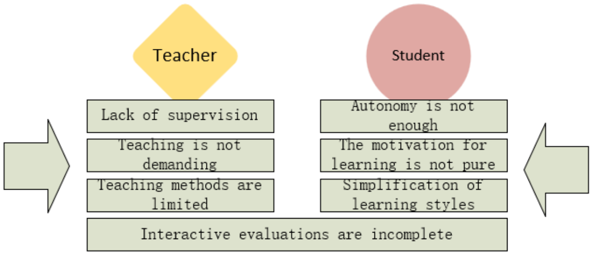


Figure 2 Diagram of the relationship between the elements of the blended learning model and the problem

As can be seen from Figure 2, from the teacher's perspective, the current blended learning approach, due to the network, the teacher's supervision is insufficient, is not strong enough for their teaching literacy, and the teaching style is somewhat lacking, which is not enough to drive the students' motivation; from the student's perspective, the current blended learning approach leads to the students' lack of autonomy, lack of motivation, and at the same time, the cause and orientation of the learning are not conducive to independent learning, and the Learning mode is relatively single.

## 3.2 Cultivation of Independent Learning Abilities of Multimodal College Students

Aiming at the insufficiency of blended learning modes, this paper proposes a multi-mode approach to cultivating college students' independent learning abilities. This method qualitatively analyzes the college students' autonomous learning ability cultivation method from four modal techniques, specifically including the learning time management mode, the learning progress customization mode, the learning activity operation mode, and the learning behavior supervision mode, which are described as shown in Figure 3.

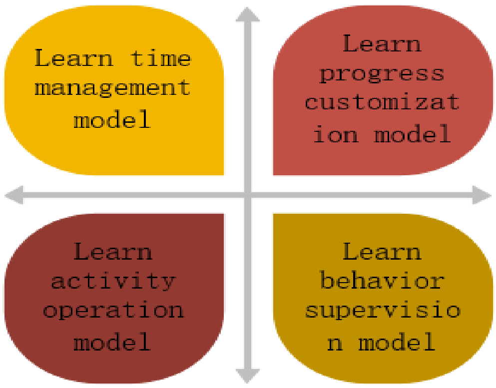


Figure 3 Schematic diagram of multimodal cultivation of independent learning ability of university students

(1) Learning time management model

College students learning time management mode refers to their ability to manage and plan their time in independent learning. In the age of informatization, college students' independent study time management is a prominent difficulty, and weak time management ability will lead to independent study being the opposite of the expected effect. To address the current phenomenon of inadequate management of independent study time, the proposed strategy of students' autonomous study time management mode, students should develop a separate study schedule based on the combination of online and offline, which includes the date, study tasks, planned study time, actual study time, time utilization, self-analysis, solutions and so on. At the same time, to improve learning efficiency and learning behavior, students should record the weekly learning activities and summarize them in categories.

(2) Learning Progress Customization Mode

(Definition, purpose, characteristics, specific measures for the customization of the progress of independent learning for university students)

The customization of college students' learning progress refers to the learning management ability of college students to grasp the learning speed by themselves according to their own learning ability and understanding level in the process of independent learning based on the combination of online and offline education. On the one hand, the large amount of information in the current wisdom is conducive to students' comprehensive mastery of knowledge. However, on the other hand, it brings the danger of deviation to students, which wastes students' learning time and energy. To solve the above shortcomings, the learning progress customization mode strategy is proposed, which requires college students to make self-adaptive learning progress and plan according to their learning characteristics; it involves college students knowing their learning progress at all times and adjusting their learning plan and arrangement in time; requires college students to record their learning progress and summarize their learning experience actively.

(3) Operational model for learning activities

College students learning activity operation mode refers to the learning behaviors or communication and cooperation with other individuals that college students carry out to accomplish a specific learning goal. Independent learning activities or behaviors generally include cooperative communication activities, online reading activities, resource summarization activities, information recording activities, and so on. The current independent learning activities based on the combination of online and offline are faced with the characteristics of the weak supervisory role of online learning activities, which makes the independent learning behaviors and management capabilities poor. To solve the above shortcomings, the learning activity operation mode strategy is proposed to improve college students' learning activity operation ability by doing reading records and summaries, independent communication and discussion, and other learning strategies.

(4) Learning behavior monitoring model

College students learning behavior supervision mode refers to college students' perception, recording, analysis, feedback, and regulation of learning behavior and psychological situation in the process of independent learning, and the specific self-monitoring process is shown in Figure 4. According to the questionnaire analysis, online college students need a stronger sense of self-learning monitoring. In the face of rich and diverse resources, students cannot make good use of the supervision and management of their behavior, which can easily lead to learning pressure, thus affecting learning efficiency. To solve the above deficiencies, the learning behavior supervision model strategy is proposed, paying attention to the process observation, feedback, and adjustment of different learning contents or stages and the supervision and control of students' learning behavior through external individuals.

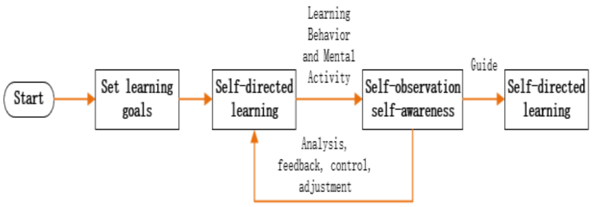


Figure 4 Schematic diagram of multimodal cultivation of college students' independent learning ability

# 4 Methods of Cultivating College Students' Independent Learning Ability Based on Multimodal Integration

To quantitatively optimize the cultivation strategy of college students' autonomous learning ability based on multimodal fusion, this paper combines the butterfly optimization algorithm to quantify the fusion of the cultivation strategy of college students' independent learning ability. It proposes a method based on multimodal fusion.

## 4.1 Butterfly optimization algorithm

BOA (Butterfly optimization algorithm) is a new nature-inspired global optimization algorithm [22] inspired by butterflies' foraging and courtship behavior. The behavior of butterflies can be described as their concerted movement toward the location of food sources and courtship objects by receiving, sensing, and analyzing scents in the air to determine the potential direction of a food source or a mating object.BOA mimics this behavior to find the optimal location in the search space. To model the behavior of butterflies, the behavior was simplified into the following features.

(1) All butterflies can give off scent and can attract each other

(2) Each butterfly will move randomly or in the direction of the best butterfly with the highest concentration of scent.

(3) The objective function influences the stimulus intensity of butterflies.

The calculation of scent is an essential part of the whole algorithm, which has three main important variables: sensory modality ( $c$ ), stimulus intensity ( $I$ ), and power index ( $a$ ). BOA $I$ is closely related to the fitness value of butterflies, meaning that when a butterfly emits a strong scent, the surrounding butterflies can sense it and move closer to it. $a$ is a parameter that affects the intensity of the stimulus, allowing for regularized expression, linear response, and response compression. Response expansion is when $I$ increases when the scent ( $f$ ) increases faster than $I$ . Response compression is when $I$ increases when $f$ increases slower than $I$ . Linear response is when $I$ it increases and $f$ increases proportionally. Biologists, through many studies on insects, humans, and animals, have concluded that sometimes, as a stimulus becomes very strong, the insect becomes less and less sensitive to the stimulus change. Therefore, in BOA, response compression is used to estimate the range $I$ .

According to Steven's power law. The weaker butterflies move towards the more vital butterflies and increase faster $I$ . Therefore, $f$ is varies with scent absorption, and the degree of absorption is determined by $a$ .

$$f = cI^a \tag{1}$$

Where $a \in [0,1]$, when $a = 1$ means that other butterflies can perceive the scent emitted by a particular butterfly with the same ability. When $a = 0$ used, the smell emitted by one specific butterfly cannot be perceived by other butterflies. Therefore, $a$ is controls the behavior of the algorithm. $c$ is an important parameter that determines the speed of convergence of the algorithm and the performance of BOA performance.

BOA is divided into three phases: an initialization phase, an iteration phase, and a completion phase. In each run of BOA, the initialization phase is executed first. Then, the search is iteratively performed in space until the best position is found, the objective function value is optimal, and the algorithm is terminated.

In the initialization phase, the algorithm defines the objective function and its solution space, sets the initial parameters of the BOA, and then performs an iterative optimization with the initial butterfly population distribution, which requires the allocation of a fixed memory for storing their scent and fitness values since the number of butterfly populations stays the same during the iteration process.

The iterative phase is performed by the algorithm for several iterations. In each iteration, all the butterflies in the search space are shifted to new locations, and their fitness values are evaluated. The algorithm first calculates all the fitness values at different places in the solution space, and then these butterflies generate new flavors at their sites according to equation (1). The algorithm has two main vital steps: the global search phase and the local search phase. In the worldwide search phase, the butterflies are approached towards the butterfly with the best fitness ( $g^*$ ), which is calculated as follows:

$$x_i^{t+1} = x_i^t + (r^2 \times g^* - x_i^t) \times f_i \tag{2}$$

Where $x_i^t$ is the solution vector $x_i$ for the $i$ butterfly in the first iteration $t$ , where $g^*$ represents the current optimal solution found in the space of all keys in the current iteration? The flavor of the $i$ butterfly is denoted by $f_i$ and $r$ is a random number[0,1].

The localized search phase can be represented as:

$$x_i^{t+1} = x_i^t + (r^2 \times x_j^t - x_k^t) \times f_i \tag{3}$$

Where $x_j^t$ are the $i$ and $k$ th butterflies in the solution space? If $x_j^t$ and $x_k^t$ belongs to the same cluster and $r$ is a random number[0,1], then equation (3) is a localized random wandering.

Butterflies searching for food and mating partners can be done on all local and global scales. Considering its reasons and various other factors like wind, rain, etc., searching for food has an essential part in the whole search activity of butterflies to find mating objects or food $p$ . Therefore, switching probability $p$ is used in the BOA algorithm to switch between ordinary global search and intensive local search.

The algorithm does not stop iterating until a termination condition is reached. Different stopping criteria can be defined, such as the maximum CPU time used, the maximum number of iterations, matching a specific error rate, or other suitable criteria. At the end of the iteration, the algorithm will output the optimal solution with the best fitness value. The above three steps constitute the complete flow of the BOA algorithm, the pseudo-code of which is shown below:

Table 1 Butterfly optimization algorithm pseudo-code

| **Butterfly Optimization Algorithm Pseudo-code** |
|---|
| The fitness function $f(x)$, the $x = (x_1, x_1, \cdots, x_{\dim})$ |
| Butterfly population initialization: $x_i = (i = 1, 2, \cdots, n)$ |
| The stimulus intensity $I_i$ is $f(x_i)$ |
| Define the feeling modality $c$, the power exponent $a$, and the switching probability. |
| If stopping conditions are not met |
| Use equation (1) to calculate the flavor of each individual in the population. |
| Look for the individual with the most pungent aroma |
| For each individual in the population, generate random numbers $r \in [0,1]$ |
| If : $r < p$ |
| Individuals move toward the optimal individual position using equation (2) |
| Else |
| Individuals use equation (3) to search locally in |
| Update the value of $a$ |
| End of Iteration |
| Output the optimal solution. |

## 4.2 Multimodal fusion method based on the butterfly optimization algorithm

In this section, the "Questionnaire on Independent Learning of College Students" is used to investigate the independent learning ability of college students. By comparing the Likert-type scores of the four modes in the questionnaire on the independent learning ability of college students before and after the use of the multimodal fusion method, the author establishes an objective function for the score difference, construct a multimodal fusion weight optimization model, and utilize the butterfly optimization algorithm to solve the questionnaire student's The adaptive multimodal fusion weights of the students in the questionnaire are solved using the butterfly optimization algorithm.

(1) Multimodal fusion weights

This section proposes four kinds of mode weights, including learning time management mode weights, learning progress customization mode weights, learning activity operation mode weights, and learning behavior supervision mode weights, which are defined as follows: 1) time management mode weights mainly focus on the management of college students' independent learning time, which is recorded as $w_1$ ; 2) learning progress customization mode weights mainly focus on the management of college students' independent learning progress, arrangement, etc., which is recorded as $w_2$ ; (3) The weight of learning activity operation mode mainly focuses on the management of college students' independent learning activity operation and so on, which is recorded as $w_3$ ; (4) The weight of learning behavior supervision mode mainly focuses on the supervision of college students' independent learning behavior and so on, which is recorded as $w_4$ .

(2) Weighted optimization objective function

To optimize the weights of learning strategies suitable for each college student surveyed by the questionnaire, this section adopts the difference between the scores of the questionnaires of the college students before and after the application of multimodal strategies as the basis for independent learning enhancement. It constructs the weight optimization objective function. The specific equation is as follows:

$$S_{all} = \sum_{t=0}^{end} \left( w_1 \left( S_t^1 - S_{t,0}^1 \right) + w_2 \left( S_t^2 - S_{t,0}^2 \right) + w_3 \left( S_t^3 - S_{t,0}^3 \right) + w_4 \left( S_t^4 - S_{t,0}^4 \right) \right) \tag{4}$$

$$w_1 + w_2 + w_3 + w_4 = 1 \tag{5}$$

Where $S_{all}$ is the value of the weight optimization objective function, $S_t^1$ $S_t^2$ $S_t^3$ and $S_t^4$ are the questionnaire scores of the $t$ th student after applying the multimodal strategy, $S_{t,0}^1$ $S_{t,0}^2$ $S_{t,0}^3$ and $S_{t,0}^4$ are the questionnaire scores of the $t$ th student before applying the multimodal strategy?

### 4.3 Optimization Process of Cultivating College Students' Independent Learning Ability Based on Multimodal Integration

According to the optimization decision variables and the adaptability function, the steps of the optimization method for cultivating college students' independent learning ability based on multimodal fusion are as follows:

Step 1: The Independent Learning Questionnaire for College Students was used to investigate the independent learning ability of college students by collecting Likert-type scores for the four modes before applying the multimodal strategy;

Step 2: Applying the multimodal strategy to the same batch of students, the Independent Learning Questionnaire for College Students was used to investigate the independent learning ability of college students and collect the Likert-type scores of the four modes after applying the multimodal strategy;

Step 3: Initialize the algorithm parameters, such as population parameters, number of iterations, etc., at the same time;

Step 4: Initialize the population using uniform distribution and calculate the fitness function value according to equation (4);

Step 5: The global search phase and the local search phase are used to update the butterfly individuals, compute the fitness function value, and update the global optimal solution;

Step 6: Judge whether the termination condition is satisfied. If it is comfortable, exit the iteration, output the optimal cultivation weight value, and execute step 7; otherwise, continue to complete step 5;

Step 7: Construct a multimodal fusion of the cultivation of college students' independent learning ability and give the cultivation strategy suitable for individual college students.

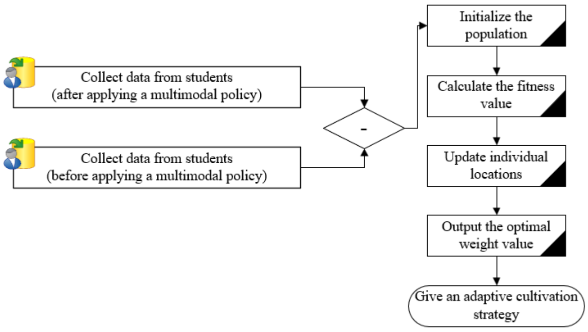


Figure 5 Flowchart for the optimization of self-directed learning development

## 5 Experiment and Result Analysis

To verify the effectiveness and superiority of the method proposed in this paper, this section applies the cultivation countermeasures to the college students involved in the case, counts the Likert-type scores of the four modes, and optimally solves for the fusion weights through comparative analysis to obtain different learning mode strategies for other college students.

### 5.1 Simulation Environment Setting

The program was written in this paper using MATLAB 2021a, and the test environment was Windows 10 with an AMD Ryzen 9 5900HX with a Radeon Graphics processor and 16.0 GB of RAM. The experimental dataset was selected to have the sample survey scores of the case colleges in the first half of 2022 as the pre-application strategy data and the 2022 sample survey scores of the case institutions in the second half of the year as the post-application strategy data. The specific parameter settings of the cultivation optimization algorithm and comparison optimization method proposed in this paper are shown in Table 2.

Table 2 Parameter settings for the multimodal fusion method

| arithmetic | parameterization |
|---|---|
| BOA | Parameter-free optimization algorithm |
| AMO | Parameter-free optimization algorithm |
| WCA | Nsr=8, dmax=0.001, μ=0.1 |
| LSA | Channel time is 10 |
| GO | a=2-2×(iter/intermix) |

### 5.2 SOA Optimization Weight Simulation

To verify the feasibility and effectiveness of BOA optimizing multi-mode cultivation weights, the survey scores before and after applying multi-mode cultivation strategies in the case universities are selected as input data for BOA optimization weight analysis. The number of populations and the maximum number of iterations of the algorithms are set to 20 and 500, respectively, and each algorithm optimizes each cultivation strategy weight independently 20 times.

The results of weight optimization for multi-strategy cultivation are given in Figure 6-Figure 9. Table 3 shows the statistical results of the number of weight optimization evaluations. From Figures 6-9, it can be seen that BOA is the first to optimize to obtain the optimal values of the four modes of weight optimization, which is significantly faster than the other optimization algorithms. From Table 3, it can be seen that BOA obtains the optimal objective function values for weight optimization, including learning time management mode, learning progress customization mode, learning activity operation mode, and learning behavior supervision mode at the 16th, 20th, 35th, and 46th evaluation times respectively, which is better than the comparison algorithms; the number of evaluations required for BOA to obtain the optimal values is ranked first. In conclusion, NRO converges faster than other optimization algorithms and gets the best weight optimization results.

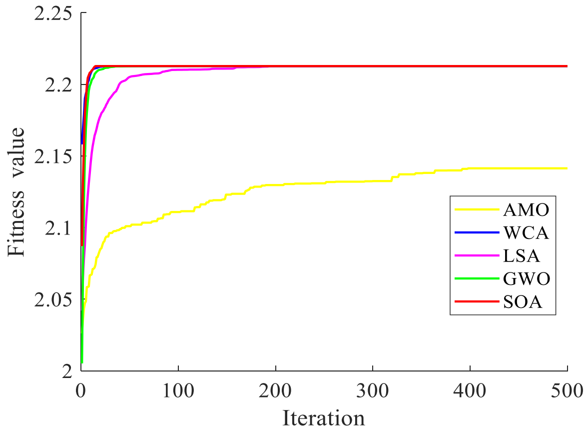


Figure 6 Optimization process of learning time management model

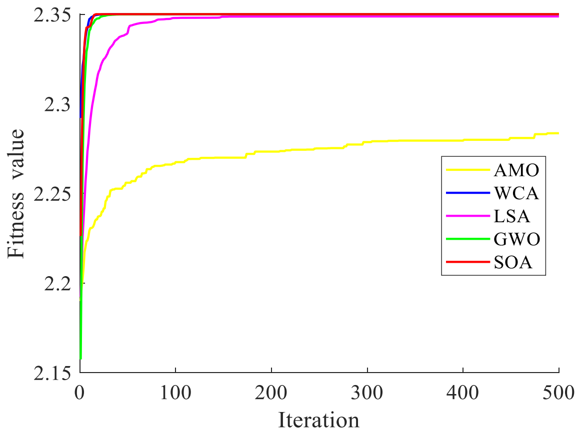


Figure 7 Optimization process of learning progress customization model

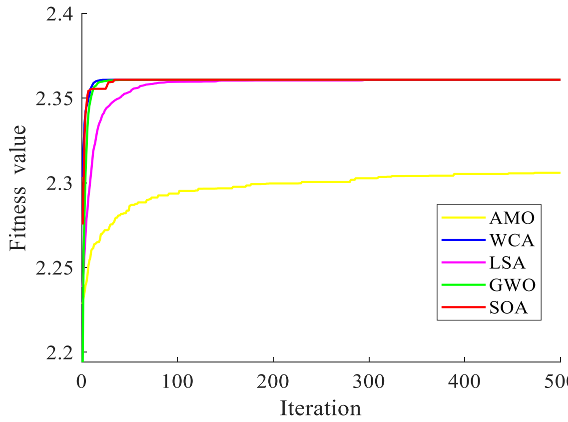


Figure 8 Optimization process of learning activity operation mode

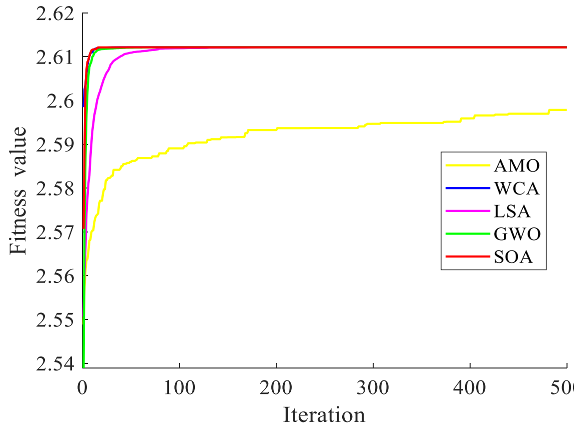


Figure 9 Optimization process of learning behavior supervision model

Table 3 Number of weight optimization evaluations for each model state

| modalities | AMO | WCA | LSA | GO | SOA |
|---|---|---|---|---|---|
| Learning time management model | 398 | 121 | 484 | 498 | 16 |
| Learning Progress Customization Mode | 496 | 108 | 495 | 500 | 20 |
| An operational model for learning activities | 473 | 158 | 472 | 498 | 35 |
| Learning Behavior Monitoring Model | 482 | 82 | 499 | 499 | 46 |
| Average ranking/overall ranking | 5/5 | 3/3 | 5/5 | 7/7 | 1/1 |

## 5.3 Optimization weighting analysis

To verify the robustness of the optimized weights, this paper selects 200 case college students as survey samples, statistically analyzes the questionnaire scores before and after applying the multi-mode strategy, and optimizes and fuses the statistical data by using the BOA algorithm to obtain the optimized weights of the four modes. At the same time, the weighting errors are given before and after the application, as shown in Figures 10 and 13. Figures 10-13 show that the overall trend of the four weights after optimization is similar to the general direction before optimization.BOA is robust in optimizing the weights, and at the same time, it can be seen from the four modes that the weight error of BOA optimization can be controlled within 0.2, which achieves the effect of optimizing the weights.

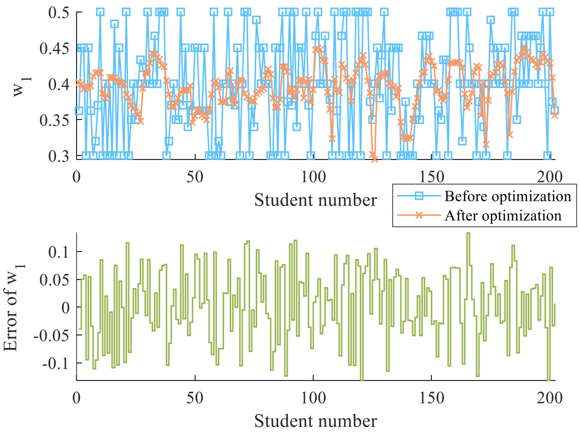


Figure 10 Learning time management model weighting analysis

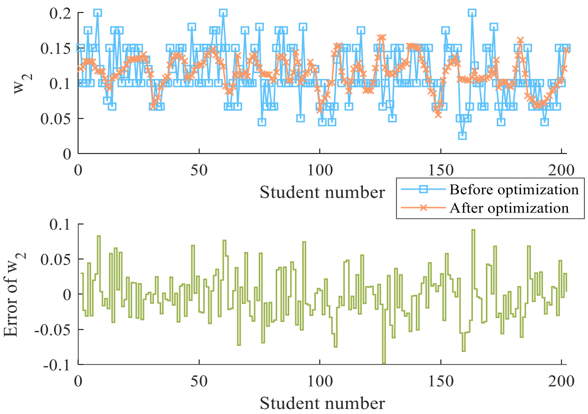


Figure 11 Learning progress customization model weighting analysis

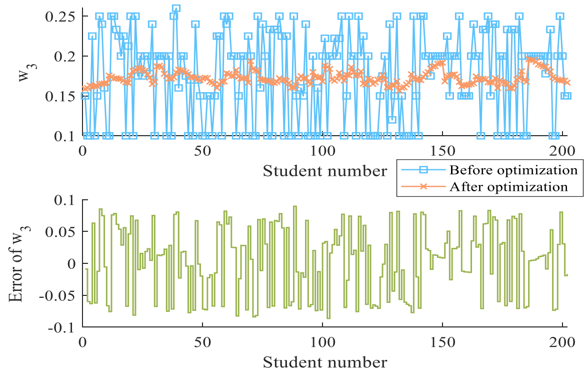


Figure 12 Analysis of the weights of the operational model of learning activities

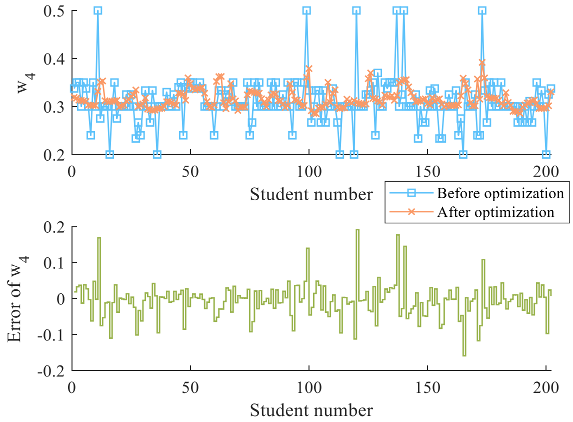


Figure 13 Learning behavior supervision model weighting analysis

## 6 Conclusion

Aiming at the problems existing in the current blended mode of college students' independent learning, this paper proposes a multi-mode fusion independent learning ability cultivation method based on the BOA optimization algorithm. The technique analyzes the autonomous learning mode of college students, introduces in detail the deficiencies of the blended learning mode, puts forward the countermeasure scheme for the cultivation of the independent learning ability in four ways, and uses the butterfly optimization algorithm to optimize the weights of the cultivation of independent learning ability of college students. Through experimental analysis, the multi-mode fusion autonomous learning ability cultivation proposed in this paper is adequate and robust. The cultivation fusion algorithm is easy to fall into the local optimum, so the next research step focuses on improving the optimization performance of the algorithm.

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