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A Self-learning Ability Assessment Method Based on Weight-Optimised Dfferential Evolutionary Algorithm

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Abstract

INTRODUCTION: The research on the method of cultivating college students' autonomous ability based on experiential teaching is conducive to college students' change of learning mode and learning thinking, improving the utilisation rate of educational resources, as well as the reform of education.
OBJECTIVES: Addressing the current problems of unquantified analyses, lack of breadth, and insufficient development strategies in the methods used to develop independent learning skills in university students.
METHODS: This paper proposes an intelligent optimisation algorithm for the cultivation of college students' independent learning ability in experiential teaching. Firstly, the characteristics and elements of college students' independent learning are analysed, while the strategy of cultivating college students' independent learning ability in experiential teaching is proposed; then, the weight optimization method of cultivating college students' independent learning ability based on experiential teaching is proposed by using the improved intelligent optimization algorithm; finally, the validity and feasibility of the proposed method are verified through experimental analysis.
RESULTS: The results show that the proposed method has a wider range of culture effects.
CONCLUSION: Addressing the problem of poor generalisation in the development of independent learning skills among university students.

Keywords: college students' independent learning ability cultivation, experiential teaching, differential evolutionary algorithm, weight optimisation

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1. Introduction

With the rapid development of computer technology and artificial intelligence algorithms, the cultivation mode of college students' independent learning ability based on the Internet and artificial intelligence technology has developed rapidly. The traditional method of independent learning ability of college students has been unable to meet the needs of college students' learning [1]. The supporting role of computer and information technology makes college students' independent learning more efficient and solves the limitations of place, time and way of traditional learning mode [2]. Based on the experiential teaching of college students' independent ability cultivation is a teaching method aimed at cultivating college students' independent learning ability and problem solving ability by letting students participate in the practice and experience personally [3]. The research on the method of cultivating college students' independent ability based on experiential teaching is conducive to college students' changing their learning styles and thinking, improving the utilisation rate of educational resources, and also conducive to the reform of education [4]. Therefore, studying the cultivation of college students' autonomous ability based on experiential teaching is an urgent research topic [5].

The independent learning ability of college students based on experiential teaching is mainly that college students, with practical education as the main focus, without the supervision of others, set learning goals independently, adopt suitable learning methods for themselves, carry out diversified learning activities, and summarize and analyse their learning behaviours at the end of learning [6]. Currently, the methods of experiential teaching for the cultivation of college students' autonomy are divided into literature research method, observation method, survey method, interview method, case study method, and fusion method based on intelligent optimisation algorithm [7]. Literature [8] describes the four characteristics of independent learning, including mobility, independence, effectiveness, and relativity; literature [9] defines the characteristics of independent learning, and at the same time, according to the differences of individuals, adopts different learning methods and learning paths to achieve the learning goals; literature [10] constructs an independent learning scale based on Zimmerman's theory of independent learning, and conducts research from two aspects, namely, learning strategies and motivation; literature [10] builds an independent learning scale according to Zimmerman's theory of independent learning, and conducts research from two aspects, including learning strategies and motivation. Literature [11] used the Independent Learning Questionnaire for College Students to analyse the independent learning ability of college students based on the Internet and gave corresponding strategies; Literature [12] divided the independent learning ability into seven dimensions, including motivation, method, time, behaviour, environment, cooperative learning and resources, and formed the final version of the independent learning questionnaire for college students; Literature [13] Using college students' self-directed learning e-documents, the characteristics and applications of e-documents are analysed; Literature [14] summarizes the composition of college students' self-directed learning ability based on the network state and gives the cultivation methods to improve self-directed learning ability; Literature [15] analyses the elements of college students' self-directed learning ability, and gives the solutions to the improvement of self-directed learning. Analysed by the above literature, there are the following deficiencies in the current approach to the cultivation of college students' independent ability: 1) the method of cultivating college students' independent learning ability is not quantitatively analysed; 2) the literature of the study lacks breadth; 3) the independent learning method is only given to the analysis of the ability, and does not give a substantive and quantifiable cultivation strategy [16].

Differential Evolution Algorithm (DE) [17] is an efficient global optimisation algorithm which is a population-based heuristic search algorithm. Each individual corresponds to a solution vector and evolves through mutation, hybridisation and selection operations. The differential evolution algorithm is similar to the genetic algorithm, but the specific operations are defined differently. Aiming at the above problems in the cultivation method of college students' independent learning ability based on experiential teaching, this paper proposes the cultivation method of college students' independent learning ability based on intelligent optimisation algorithm for experiential teaching.

The main contributions of this paper are (1) analysing the characteristics and elements of college students' independent learning; (2) proposing the strategy of cultivating college students' independent learning ability in experiential teaching; (3) proposing a weight optimization method for cultivating college students' independent learning ability based on experiential teaching by using the improved differential evolution algorithm; and (4) verifying the method of this paper is effective and feasible through experiments.

2. Elements for the development of autonomy in university students

In order to improve the efficiency of the method of cultivation of college students' autonomy, this section selects the elements of cultivation of college students' autonomy by analysing the characteristics of college students' autonomy.

2.1. Characterisation of university students' capacity for independent learning

Independent learning ability of college students can be defined as the university in the completion of undergraduate professional courses at the same time, independently and autonomously to complete the learning objectives and tasks set independently, in the learning process based on the learning process timely adjustment of the learning plan and objectives, and ultimately form a summary of the results of learning [18].

Characterisation of college students' self-directed learning ability is to study and analyse the status of college students' self-directed learning ability in the network environment. According to the analysis of the information results of the literature survey, the characteristics of college students' independent learning ability include:

(1) Autonomy: college students have a strong sense of independent learning and ability in the network environment, and are able to take the initiative to choose learning resources and learning modes, and complete learning tasks independently.

(2) Learning motivation: college students' independent learning ability in the network environment is closely related to their learning motivation. Positive learning motivation can encourage college students to participate in learning activities more actively and improve their independent learning ability.

(3) Learning strategies: college students need to master certain learning strategies in the network environment, such as the ability to search, organise and evaluate information, as well as problem solving and critical thinking skills, which help to improve independent learning ability.

(4) Learning resources utilisation: college students can make use of rich learning resources in the network environment, such as online courses, e-books, academic papers, etc., to improve their independent learning ability.

(5) Assessment of learning outcomes: college students need to have the ability to assess learning outcomes in the network environment, to be able to self-reflect and adjust their learning strategies, and to improve their independent learning ability.

To summarise, the characteristics of university students' self-directed learning ability in the online environment include autonomy, learning motivation, learning strategies, learning resource utilisation and learning outcome assessment, as shown in Figure 1.

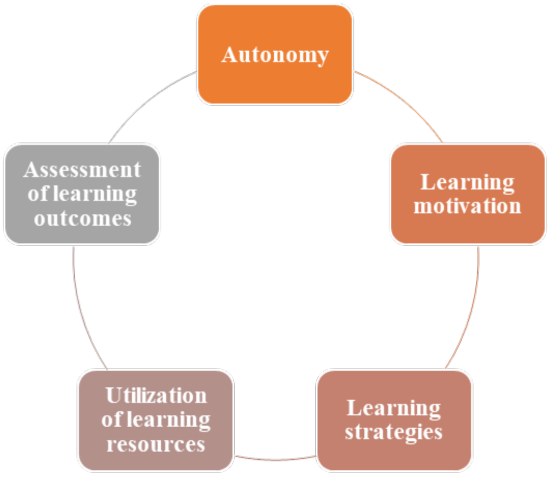

Figure 1. Characteristics of university students' self-directed learning ability

2.2. Selected Elements of Independent Learning Competencies for University Students

College students' independent learning ability is analysed from five aspects of the ability elements such as motivation, learning method, learning time, learning environment and sociality [19]:

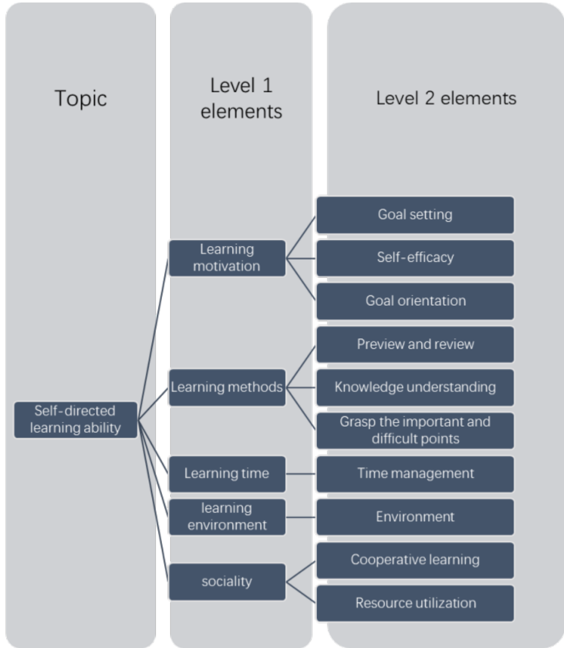

Figure 2. Analysis of the elements of independent learning ability of university students

(1) Learning Motivation

Motivation of college students for independent learning indicates why college students undertake independent learning and is implemented through intrinsic or self-initiated motivation, with specific elements including goal setting, self-efficacy, and goal orientation [20].

(2) Learning Methods

College students' independent learning methods indicate how college students carry out their studies, either through planned or automated selection of methods suitable for them, with specific elements including pre-study and review, knowledge comprehension, and grasping of important and difficult points [21].

(3) Study time

College students' independent study time indicates how college students manage their time in the process of conducting independent study, which is through timed and effective time management methods, and specific elements include time management methods [22].

(4) Learning environment

The independent learning environment for university students indicates where university students carry out their independent learning process, through conscious and selective management of the social environment, with specific elements including environmental management methods.

(5) Social

The social aspect of self-directed learning for college students indicates with whom college students engage in learning exchanges, through conscious and selective management of the social environment, with specific elements including co-operative learning and resource utilisation.

3. Strategies for Cultivating College Students' Independent Learning Ability under Experiential Teaching

Based on the analysis of the elements of independent learning of college students in the previous section, this subsection analyses the deficiencies of the current methods of independent learning ability cultivation and proposes a strategy for cultivating independent learning ability of college students based on experiential teaching.

3.1. Deficiencies in the cultivation of independent learning ability of current university students

According to the questionnaire survey analysis, combined with the independent learning activities of college students, there are deficiencies in the current cultivation of independent learning ability of college students [23]:

(1) College students' motivation for independent study is not clear. The current college students are not interested in the undergraduate programme, and they study their majors not for hobby or from the attraction and guidance of the teachers, but for the sake of getting good grades and getting the required credits.

(2) College students' independent study programmes are unreasonable. Currently, college students do not know enough about the importance of the study plan, and the arrangement of the plan is unreasonable, and most of them cannot complete the content of the plan.

(3) College students' independent study methods are not efficient. Although the current college students have plans, the implementation rate of the plans is not enough, which boils down to the fact that the learning methods are not adapted to the implementation of the plans, and the rate of self-consciousness of the implementation of the plans is not high.

(4) College students' independent learning interaction is not strong. Currently, college students are more independent, and in the face of problems, they are less motivated to discuss them with teachers and classmates, and they are not sufficiently integrated with reality.

3.2. Strategies for Cultivating Students' Independent Learning Ability Based on Experiential Teaching

The development of college students' autonomy based on experiential teaching is a teaching method that aims to develop their independent learning ability and problem-solving ability by engaging students in hands-on practice and experience [24].

Based on the above literature review, the development of college students' autonomy based on experiential teaching can be implemented in the following ways:

(1) Connecting with life to stimulate interest. Combine the content of the curriculum with students' life experience and interests, and design interesting practical activities to stimulate students' interest in learning.

(2) Adjustment of teaching content. According to the learning needs and ability level of students, the teaching content is reasonably adjusted to ensure that students can understand and master the knowledge.

(3) Individualised teaching and learning. Individualised teaching methods and strategies are used for different students to meet their learning needs and development potential.

(4) Fostering a sense of creativity. Encourage students to think and ask questions to develop their sense of creativity and problem-solving skills.

(5) Independent enquiry. Provide students with opportunities and resources for independent learning and encourage them to take the initiative to explore and discover knowledge.

The specific description of the strategy for developing college students' autonomy based on experiential teaching is shown in Figure 3.

Figure 3. Strategies for cultivating college students' independent learning ability based on experiential teaching

4. Population Linear Reduction Differential Evolutionary Algorithm

In order to optimise the cultivation strategy of college students' independent learning ability based on experiential teaching, this paper combines the population linear reduction differential evolution algorithm (Success-history based adaptive differential evolution algorithm with linear population size reduction, LSHADE) to quantify the fusion of experiential teaching cultivation strategies, and proposes a multi-modal fusion-based method.

The LSHADE algorithm is an efficient and improved version of the DE [25] algorithm. In the optimisation process, the LSHADE algorithm uses variation, crossover, and selection operators to find the global optimum.The advantages of the LSHADE algorithm are its fastness and robustness [26].The LSHADE algorithm won the first place in the IEEE CEC 2014 unconstrained single-objective standard test. In IEEE CEC Evolutionary Computation Conference, LSHADE was improved many times and achieved better results.LSHADE algorithm mainly uses adaptive success history memoriser strategy with population linear reduction strategy to improve the performance of DE. The main steps are as follows:

Step 1: Initialise the population.

$$x_{i,j}^{0}=lb_j+rand\cdot\left(ub_j-lb_j\right) \tag{1}$$

Where $rand$ denotes a random number between 0 and 1; $x_{i,j}^{0}$ denotes the j^{th} dimension $\left(j=1,2,\cdots,D\right)$ of $\left(i=1,2,\cdots,N\right)$ the i^{th} intelligence in the initial population; lb_j and ub_j denote the upper and lower bound ranges of the jth dimension of the vector.

Cr F Step 2: Set the Cross Rate and Scale Factor control parameters.

$$Cr_i=randn\left(Mcr_i,0.1\right) \tag{2}$$

$$F_i=randc\left(MF_i,0.1\right) \tag{3}$$

Where $randn\left(Mcr_i,0.1\right)$ and $randc\left(MF_i,0.1\right)$ denote random numbers Mcr with mean and variance 0.1 that obey normal and Cauchy distributions, respectively; Mcr and MF denote the mean values of the success Cr history and F parameters, respectively, that are randomly selected from a M memristor ; Mcr and MF are initially set to 0.5 and will be updated according to Eqs. (2) and (3) as the number of iterations increases.

Step 3: Generate the mutation vector v_i^G . Propose a new mutation strategy based on the current-to-pbest/1 mutation strategy:

$$v_i^G=x_i^G+F_i^G\left(x_{pbest}^G-x_i^G\right)+F_i^G\left(x_{r1}^G-x_{r2}^G\right) \tag{4}$$

Where x_i^G denotes the i^{th} target vector G of the generation; F_i^G denotes the ith scale factor of the G generation; x_{pbest}^G is a randomly selected one of the optimal p target vectors, where p-value is an important control parameter for balancing the exploration and prospecting; $r1$ is a random index of the individuals in the current population; $r2$ denotes a random index of the individuals in the population after merging the current population with the external archive, which contains the better vectorised individuals from the previous iterations.

Step 4: Execute the crossover operator.

$$u_{i,j}^G=\begin{cases}v_{i,j}^G & if\left(rand_{i,j}\le Cr_i\ or\ j=j_{rand}\right)\\ x_{i,j}^G & otherwise\end{cases} \tag{5}$$

where the crossover rate Cr_i determines whether the variable integrates the variable values of the variant vector; j_{rand} denotes a uniformly distributed random number between $\left[1,D\right]$ to ensure that at least one of the variables of the test vector comes from the variant vector to avoid the DE falling into a local optimum.

Step 5: Select the better vector to build a new population. This greedy strategy is represented as follows:

$$x_i^{G+1}=\begin{cases}u_i^G & if\left(f\left(u_i^G\right)\le f\left(x_i^G\right)\right)\\ x_i^G & otherwise\end{cases} \tag{6}$$

x_i^{G+1} denotes the new vector of the next generation, $f\left(u_i^G\right)$ and $f\left(x_i^G\right)$ denote the fitness function values of u_i^G and x_i^G , respectively.

Step 6: Update the population size size. To improve the efficiency of DE, Linear population size reduction (LPSR) strategy was used.

$$N^{G+1}=round\left[\left(\frac{N^{\min}-N^{init}}{\max\_nfes}\right)\cdot nfes+N^{init}\right] \tag{7}$$

Where $nfes$ and $\max\_nfes$ denote the current and maximum number of evaluations; $round$ denotes the rounding function; N^{init} denotes the initialised population size; and $N^{\min}$ denotes the minimum number of populations, which is normally set to 4.

Step 7: If the current $nfes$ number of evaluations reaches the maximum $\max\_nfes$ number of evaluations, stop the optimisation process and output the optimal solution.

5. A method of cultivating college students' independent learning ability based on LSHADE integration of experiential teaching

In order to verify the effectiveness and superiority of the proposed method in this paper, this section applies the strategy of cultivating college students' independent learning ability by experiential teaching and counts the Likert-type scores of 10 elements in five aspects, and optimally solves for the fusion weights through comparative analysis to verify the effectiveness of the proposed strategy.

5.1. A Multimodal Experiential Teaching and Learning Integration Approach Based on the LSHADE Algorithm

In order to verify the effectiveness of the algorithm, this section adopts the Questionnaire on Independent Learning Ability of College Students to conduct a questionnaire on independent learning ability of college students, by comparing the Likert-type scores of the 10 elements in the questionnaire on independent learning ability of college students before and after the use of experiential teaching methodology, establishing the score discrepancy objective function, constructing the optimisation model of the fusion weights, and using the LSHADE algorithm for solving the fusion weights of the questionnaire students.

Corresponding to the five aspects of learning motivation, learning methods, learning time, learning environment, social and so on, this paper puts forward the learning motivation weighting, learning methods weighting, learning time weighting, learning environment weighting, social weighting, the specific definitions are as follows: (1) learning motivation weighting mainly focuses on why college students want to learn motivation goals, recorded as w_1 ; (2) learning methods weighting mainly focuses on how to carry out the learning methods and the weight of learning method is mainly focused on the method and strategy of how to study, which is recorded as w_2; 3) The weight of learning time is mainly focused on the management of the time of independent learning activities of college students, which is recorded as w_3 ; 4) The weight of learning environment is mainly focused on the management of the environment of independent learning of college students, which is recorded as w_4; and 5) The weight of sociality is mainly focused on the management of the interaction of independent learning of college students, which is recorded as w_5.

In order to optimise the weights of learning strategies suitable for each university student surveyed, this section uses the difference between the university students' questionnaire scores before and after applying experiential-based teaching strategies as the weight optimisation objective function:

$$S_{all}=\sum_{t=0}^{end}\left(w_1\left(S_t^1-S_{t,0}^1\right)+w_2\left(S_t^2-S_{t,0}^2\right)+w_3\left(S_t^3-S_{t,0}^3\right)+w_4\left(S_t^4-S_{t,0}^4\right)+w_5\left(S_t^5-S_{t,0}^5\right)\right) \tag{8}$$

$$w_1+w_2+w_3+w_4+w_5=1 \tag{9}$$

S_{all} Where is the value of the weighted optimisation objective function, S_t^1, S_t^2, S_t^3, S_t^4 and S_t^5 are the questionnaire scores of the t th student after applying the experiential teaching strategy, and $S_{t,0}^1$, $S_{t,0}^2$, $S_{t,0}^3$, $S_{t,0}^4$ and $S_{t,0}^5$ are the questionnaire scores of the t th student before applying the experiential teaching strategy.

5.2. Optimisation Process of Multimodal Experiential Teaching Integration Training Based on LSHADE Algorithm

According to the optimisation decision variables and fitness function, the flow chart of the optimisation method of experiential teaching integration training based on the LSHADE algorithm is shown in Figure 4, and the specific steps are as follows:

Step 1: According to the Questionnaire on Independent Learning of College Students, a questionnaire on the independent learning ability of college students in the case university was conducted to obtain the Likert-type scores before applying experiential teaching strategies;

Step 2: Cultivate the same batch of students using experiential teaching strategies, still based on the Questionnaire for Independent Learning of College Students on the independent learning ability of college students, and obtain the Likert-type scores after applying experiential teaching strategies;

Step 3: Initialise the population as well as the number of iterations;

Step 4: Calculate the value of the fitness function;

Step 5: Set the cross rate and scale factor control parameters;

Step 6: Generate the variation vector according to the current-to-pbest/1 variation strategy;

Step 7: Execute the crossover operator;

Step 8: Use the greedy strategy to select the better vector to build a new population;

Step 9: Judge whether the termination condition is satisfied. If it is satisfied, exit the iteration, output the optimal cultivation weight value, and execute step 10, otherwise continue to execute step 4;

Step 10: Construct the model of cultivating college students' independent learning ability in experiential teaching according to the weight value of superior cultivation.

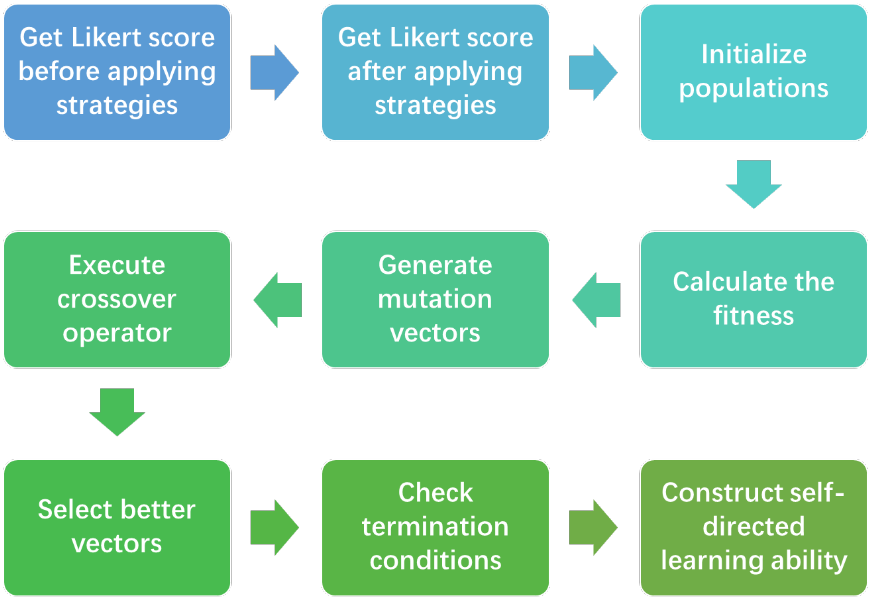

Figure 4. The optimisation of self-directed learning development

6. Results and Discussion

In order to verify the feasibility and validity of the model for the cultivation of college students' independent learning ability proposed in this paper, the results of the Questionnaire on Independent Learning of College Students were used to carry out simulation analysis.

6.1. Simulation Environment Setting

In this paper, MATLAB 2021a is used for programming, and the test environment is Windows 10 system with 16.0 GB of memory.The experimental dataset is selected from the sample survey scores of the case colleges in the first half of the year 2023 as the pre-strategy application data, and the sample survey scores of the case colleges in the second half of the year 2023 as the post-strategy application data. The specific parameter settings of the cultivation optimisation algorithm and comparison optimisation method proposed in this paper are shown in Table 1.

Table 1. Parameter settings for culture optimisation methods

arithmetic	parameterisation
LSHADE	$_{F}{}^{initinit}$H=6, M =0.5, p =0.11, N =$18D$
jSO	$_{F}$Using the variation strategy current-to-pbest-w/1, H=5, M =0.3, the $^{init\mathrm{min}initinit}$p =0.25, p =p /2, N =25log(D)(D)$^{0.5}$
GEDGWO	parameterisation
NRO	$_{Fi\beta}$p =0.75, p =0.1, freq=0.05, Adoption of the Levy distribution strategy
SOS	parameterisation
TLBO	parameterisation

6.2. Simulation analysis

In order to verify the feasibility and effectiveness of LSHADE optimising cultivation weights, the survey scores before and after the experiential teaching cultivation strategy of the case university were selected as the input data for the LSHADE optimisation weights analysis. The number of populations and the maximum number of iterations of the algorithms are set to 100 and 500, respectively, and each algorithm optimises each cultivation strategy weight independently for 20 runs. The results of the cultivation weight optimisation are given in Figure 5

As can be seen from Figure 6, the experiential teaching cultivation optimisation based on the LSHADE algorithm converges the fastest, obtaining the optimal objective function value at the 16th iteration number, and solving for the optimal weight values. Figure 6 gives the number of convergence iterations for cultivation weight optimisation. From Figure 6, it can be seen that LSHADE, jSO, GEDGWO, NRO, SOS, and TLBO algorithms converge at the 16th, 20th, 35th, 46th, and 100th iterations, respectively. In conclusion, LSHADE converges faster than other optimisation algorithms and obtains the best weight optimisation results.

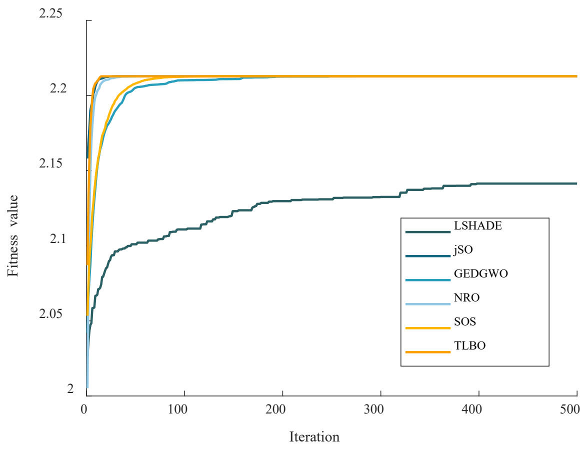

Figure 5. Convergence process of optimisation of cultivation weights

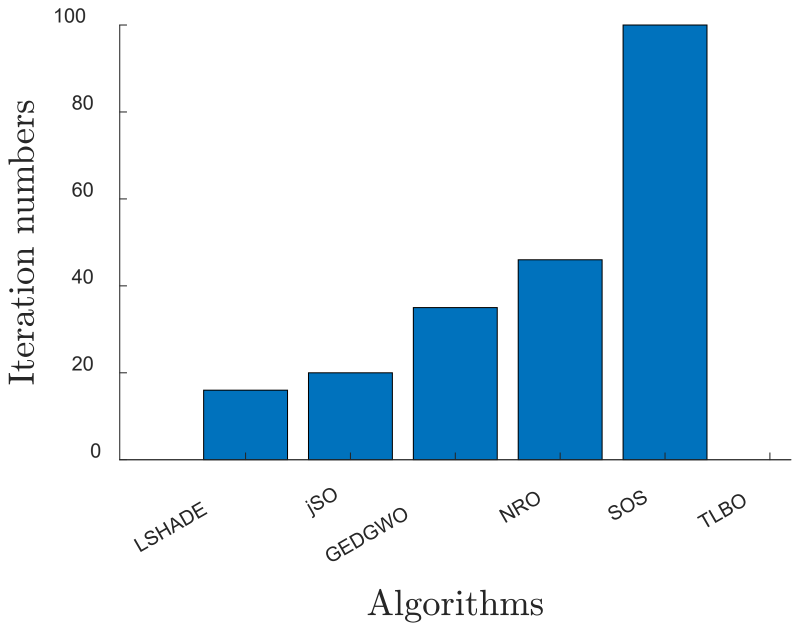

Figure 6. Number of convergence iterations for cultivation weight optimisation

In order to further verify the feasibility of optimising the weights, this paper selects 200 students from the case university as the survey sample, statistically analyses the questionnaire scores before and after the application of experiential teaching strategies, and optimally solves the statistical data by using the LSAHDE algorithm to obtain the average weight optimisation results, as shown in Figure 7. As can be seen from Figure 7 the overall trend after weight optimisation is similar to the overall trend before optimisation. The average weight error notation over is shown in Figure 8. From Figure 8, it can be seen that the error between the weight optimised value and the pre-optimisation value is controlled within 0.15, indicating that the algorithm proposed in this paper is effective and feasible.

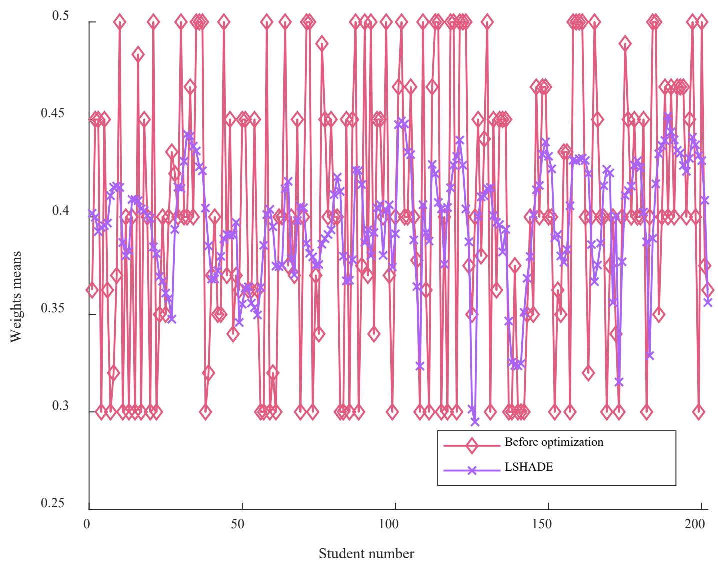

Figure 7. Weight optimisation based on LSHADE algorithm

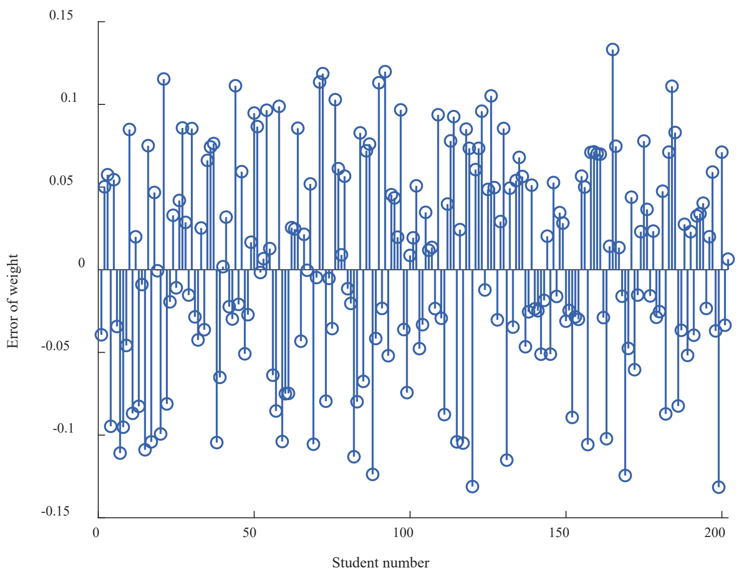

Figure 8. Weighting error based on LSHADE algorithm

7. Conclusion

Aiming at the problems existing in the current method of cultivating college students' independent learning ability, this paper proposes the method of cultivating college students' independent learning ability based on experiential teaching with the LSHADE optimisation algorithm. The method analyses the characteristics analysis and selection of elements of college students' independent learning ability, proposes five independent learning ability cultivation strategies based on experiential teaching, and optimizes the weights of college students' independent learning ability cultivation by using the LSHADE algorithm. Through experimental analysis, the cultivation of independent learning ability based on experiential teaching proposed in this paper is effective and feasible. The optimisation algorithm is easy to fall into the optimality seeking precocity, so the next research focuses on improving the optimisation efficiency of the LSHADE-based cultivation fusion algorithm.

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