

## Retraction

# Retracted: Optimization and Combination Analysis of English Multimodule Learning Strategies based on Computational Intelligence

### Security and Communication Networks

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

- (1) Discrepancies in scope
- (2) Discrepancies in the description of the research reported
- (3) Discrepancies between the availability of data and the research described
- (4) Inappropriate citations
- (5) Incoherent, meaningless and/or irrelevant content included in the article
- (6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

In addition, our investigation has also shown that one or more of the following human-subject reporting requirements has not been met in this article: ethical approval by an Institutional Review Board (IRB) committee or equivalent, patient/participant consent to participate, and/or agreement to publish patient/participant details (where relevant).

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

### References

- [1] X. Bao, "Optimization and Combination Analysis of English Multimodule Learning Strategies based on Computational Intelligence," *Security and Communication Networks*, vol. 2022, Article ID 9630353, 9 pages, 2022.

## Research Article

# Optimization and Combination Analysis of English Multimodule Learning Strategies based on Computational Intelligence

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Due to the stagnation of foreign language teaching method research and the rapid development of cognitive psychology, in the early 1970s, the research focus of foreign language teaching changed from teacher to student research. In this context, the research of English learning strategy entered the historical stage of foreign language teaching research, and the global research of foreign language learning strategy was launched. In the past 30 years, the study of English learning strategy has been a hot research topic in the field of education in China. Finally, we conclude that English learning strategy training is the result of learning strategy training. In addition, the learning strategy training also effectively improves the English learning level of the students in the experimental class. This study aims to solve the problem of optimization and combination of English learning strategies, find effective ways and implement feasible programs, and propose theoretical and practical ways in college English teaching reforms. The connotation of “multimodule” has not been given due attention, so its role has not been fully brought into play. The following questions are answered, such as “teach students complete skills,” “train students in strategies,” “treat the teaching process correctly,” “Chinese computational intelligence has many patterns, but few practical effects” and “get rid of the strange theory that cannot be taught on the basis of computational intelligence” and “let students experience the practical process of English multimodule learning strategies and applications based on computational intelligence. The problems all seem to be related to “multimodules.”

## 1. Introduction

In this study, a model for minimizing energy consumption and reducing room temperature is proposed, and an intelligent algorithm is applied to solve the nonparametric model, and experiments are used to compare the performance of three computational intelligence algorithms. The experimental results show that the particle swarm optimization algorithm is suitable for solving the proposed model [1]. The article introduces the ACO algorithm, all ACO algorithms have the same idea, and ACO is formalized as a meta-heuristic for combinatorial problems. It is foreseeable that future research on ACO will pay more attention to rich optimization problems including randomness [2]. In this study, we propose an incremental method for finding all maximizing generalized rules and adaptively modifying them as new data becomes available. The method was

developed in the context of rough set theory and is based on the early discriminability matrix idea introduced by Skowron [3]. This study proposes a new form of mathematics for dealing with complex mathematical problems arising in cognitive computing, computational intelligence, software design, and information technology. This study describes the scope and framework of reference mathematics and explains cognitive informatics and computing intelligent applications [4]. This article discusses constructivism and its role in English as a second language learning, including its main teaching methods and perspectives, and several main teaching modes. The author hopes to reveal the guiding and inspiring role of constructivism in English learning in theory and practice [5]. Worldwide, foreign language teaching, especially EFL teaching, starts at an increasingly early age and takes up more space throughout the primary and secondary school curriculum. This study

focuses on vocabulary growth in secondary schools in the eastern German state of Saxony over eight years. This study also discusses the relationship between test scores and background data, such as learning strategies, etc [6]. Based on experiments, this study analyzes the correlation between self-concept and English learning, with particular emphasis on the comparison between self-concept and spoken English. Through the recorded oral English test, according to the evaluation of the college English test oral test, the score is given first, and the experimental results show that the self-concept corresponds to the performance in English [7]. The study, which aims to describe the grammatical mistakes students make when translating Indonesian into English, was also made up of 270 students in the sixth semester, with a sample of 30 students. The findings show that the most common errors at both levels are errors in verbs; and that most errors are due to overgeneralization and ignorance of rule constraints [8]. According to preliminary research conducted by the English Learning Program, it was found that students still have problems comprehending reading texts, their ability to comprehend reading texts is still insufficient, and students' lack of ability may be caused by several factors. First, their vocabulary is still limited; second, their motivation to learn English, especially to read texts, is still low [9]. The article presents an apparatus and method for automatically optimizing a policy in a decision management system, where the end user of the system selects a portion of the policy for optimization and selects conditions for optimizing the selected portion of the policy. The decision management system then automatically optimizes selected parts of the strategy based on the selected criteria [10]. Based on the research of today's mature algorithms, this study proposes a division and multilevel clustering algorithm based on multistrategy optimization. The core idea of this algorithm is to divide all data into groups. In this process, various strategies are used to improve the clustering effect, the test shows that the algorithm is one of the best algorithms [11]. In this study, we propose a linear approximation function of unit learning curve cost to describe the budget constraint of purchasing policy optimization in mixed integer linear programming. In addition, we solve the implementation problem and provide performance comparison results [12]. This study proposes a metric space structure on a finite memory policy profile set, reveals the geometric meaning of this metric about the network structure, and studies the optimization of mixed-valued logic dynamic control systems, which consider policies with initial conditions [13]. In this study, an optimal gear management strategy for automatic transmission vehicles based on dynamic programming is proposed to study the potential fuel savings. The test results of prototype vehicles on treadmills show that significant potential fuel savings can be achieved by optimizing gear shifting, and the proposed design methods are consistent [14]. The results of this study show that business and environmental characteristics have a significant impact on the overall performance of exporting companies and the strategic applicability of their marketing mix, which means that standardization or customization is useful and will produce comparable results [15].

## 2. Strategies to Optimize Learning Methods

*2.1. The Concept of Reinforcement Learning.* Reinforcement learning usually includes the following four elements: agent, state, action, and reward value. In reinforcement learning, the actors conduct decision-making activities by monitoring the environmental state, obtain the reward values from the environmental feedback, and optimize the strategy based on the reward values obtained. An important difference between reinforcement learning and other machine learning methods is that reinforcement learning emphasizes solving the problem of continuous optimization of decision making, that is the purpose of reinforcement learning is to maximize the cumulative advantages of agents, and affirmative learning is an algorithmic framework that corrects and optimizes practice through trial and error, whose official definition is as shown in Figure 1.

The agent monitors the environmental state at time  $t$  and provides the behavioral policy at this time; when the agent's decision affects the environment, it generates a new state and sends a feedback signal to the agent that accepts the state representing  $t+1$  and returns the reward signal and continues the decision once for the next time  $t$ . This cycle is repeated until the environment indicates that the task is completed. In addition, the optimization goal of optimizing the reinforcement learning strategy has the following formula:

$$\text{maximize } \sum_t^{\infty} r_t. \quad (1)$$

In summary, the goal of amplification chemistry is to address the optimal strategy to solve the sequencing problem, which focuses more on maximizing long-term benefits while one or two decisions yield fewer benefits.

*2.2. The Markov Decision Process.* The Markov decision process inherits the Markov property, which means that the state value at the next moment of the system is only dependent on the state of the system at any given time, independent of the previous historical state. In general, Markov's decision-making process consists of four parts:

- S: A collection of all possible states in the environment, also known as spatial space
- A: Agents the collection of all possible actions, also known as the operation mode
- R:  $S \times A \rightarrow R$ : Reward function in the environment
- $\gamma$ : Discount factor

Sand A during the decision making represent sets of state and behavioral sets, respectively. Also, R is a reward value function used to calculate the reward value returned by the environment after the agent is in the state  $s$  and select the function a, and the discount factor is used to calculate the long-term gains to the broker. Starting from time  $t$ , the long-term benefits are calculated as follows:

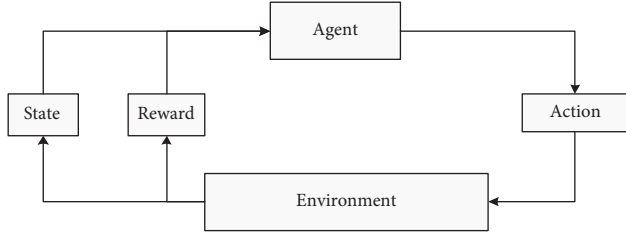


FIGURE 1: Framework diagram of the reinforcement learning algorithm.

$$R_t = \sum_{i=0}^{\infty} \gamma^i r_{t+i} = r_t + \gamma r_{t+1} + \gamma^2 r_{t+2} + \dots \quad (2)$$

An agent strategy is a probability distribution that produces different sets of reward values.

**2.3. Optimal Policy Function.** The state value function  $V_{\pi}(s)$  represents the long-term reward value generated by the agent executing the policy in state  $s$ . The specific calculation formula is as follows:

$$V_{\pi}(s) = E_{\pi} \left[ \sum_{i=0}^{\infty} \gamma^i r_{t+1+i} | S_t = s \right]. \quad (3)$$

The expression in the above formula expresses the expectation of the long-term benefit of using the policy under state  $s$  to solve the optimal policy, the formula is as follows:

$$\pi^* = \arg \max V_{\pi}(s). \quad (4)$$

The action value function  $Q_{\pi}(s, a)$  can also be used to measure the long-term reward value generated by the agent execution policy, which is a measure corresponding to the spatial value function, defined as follows:

$$Q_{\pi}(s, a) = r_{t+1} + \gamma E_{\pi} \left[ \sum_{i=0}^{\infty} \gamma^i r_{t+1+i} | S_t = s, A_t = a \right], \quad (5)$$

$Q_{\pi}(s, a)$  represents the long-term gain of the agent from agent after the state  $s$  selects and performs the function  $a$ . At this point, the optimal strategy solution formula is as follows:

$Q_{\pi}(s, a)$  represents the long-term benefit that agent obtains after agent chooses and performs the function  $a$  in state  $s$ . At this time, the optimal strategy solution formula is as follows:

$$\pi^* = \arg \max Q_{\pi}(s + a). \quad (6)$$

Regardless of whether the optimal policy is solved by the state-value function or the function is equivalent, the agent can maximize the long-term benefit in any state by implementing the optimal policy.

### 3. Learning Strategy Optimization Algorithm

**3.1. Reinforcement Learning Algorithm.** After modeling the agent-environment interaction process as the Markov decision process, according to the different strategy

optimization methods, validation learning algorithm is mainly divided into two kinds: validation learning algorithm based on value function optimization and validation learning algorithm based on policy optimization, although these two methods in different ways and focus on solving problems, but the core of their optimization agent is to maximize the cumulative return of strategy and environment interaction. Depending on whether to consider the effect of the current pattern function selection on the cumulative gain, the optimization objective can still consider maximizing the state value function or the state action value function in the current state.

The state value function represents the expected value of the cumulative benefit of the agent under the current policy when the agent is in that state, which is expressed as follows:

$$V_{\pi}(s_t) = E_{\pi} [G_t | S = s_t]. \quad (7)$$

Compared with the state value function, the state action value function measures the influence of action selection, and the expected value is specifically expressed as:

$$q_{\pi}(s_t, a_t) = E_{\pi} [G_t | S = s_t, A = a_t]. \quad (8)$$

From formulas (7) and (8), the expectation of the state value function is the state action value function on the policy F distribution, which can be expressed as:

$$V_{\pi}(s_a) = Q_t(E_{\pi}(s_1 + s_2)) = \sum_a \pi * (a_t + s) q_{\pi}(s_t, a). \quad (9)$$

In order to use the state value function and the action state function as guidance for the policy to be updated, we need to obtain the iterative relationship of these two value functions on themselves. Therefore, by extending the expression of the state-value function, you can determine the relationship as:

$$E(s_t) = E_{\pi}(R_1 + \gamma R_{t+2} + \gamma^n R_n) = E_{\pi}(R_{t+1} + R_{s_t+1}). \quad (10)$$

Similarly, the function of the state function values can be extended to obtain the iterative formula of the function:

$$q_{s+a} = E_{\pi}(R_1 + \gamma^t q(s, a_t)). \quad (11)$$

According to the Bellman equation of formula (10), the Bellman optimal equation of the next state value function  $H$  and the return function  $J$  can get the value iteration formula:

$$V_{k+1}^*(s_t) = \max_a \left( R_{s_t}^a + \gamma \sum_{s_{t+1}} \in s P_{s_t, s_{t+1}}^a V_k^*(s_{t+1}) \right), \quad (12)$$

$V_k^*$  and  $V_{k+1}^*$  are used to represent the current optimal state value function and the optimal state value function at the next moment after the update, respectively.

**3.2. Value Iteration and Strategy Evaluation.** Therefore, the main problem to be solved when using the value differential method for the strategy optimization method is the solution of the spatial value function, for which there are two main methods: the Monte Carlo method and the time series difference method. The Monte Carlo method obtains  $K$  by

sampling from the current state to the final state, using the cumulative discount as the state value function of the current state, and then making the current state value function as similar as possible. Update the policy using the sampling results as follows:

$$V_{k+1}^*(s_t) = V_k^*(s_t) + \alpha(G_t - V_k^*(s_t)). \quad (13)$$

Mathematical differentiation is a linear description of the local change rate of a function. Differentiation can be used to approximately describe how the value of a function changes when the parameter value of a function changes small enough. If there is a small change  $H$  in the variable  $X$  of the function  $F$ , then the change of the function can be divided into two parts, one is the linear part, and the other is the relational part.

In contrast, the time series difference method only uses sample data with a finite number of steps to iteratively optimize the values, for example, the upgrade strategy of the TD one-step upgrade method is as follows:

$$V_{k+1}^*s = V_k^* + \alpha + \gamma V_{k+1}^*(s_t). \quad (14)$$

The first is strategy evaluation and the second is strategy optimization. In short, the strategy-based reinforcement learning algorithm directly optimizes the size of the corresponding measures in the policy distribution according to the size of the value function. The process is as follows:

$$J(\theta) = \sum_a \in A \pi \theta(s, a) R_{s,a}. \quad (15)$$

Equation  $L$  describes the basic goal of the reinforcement learning algorithm, and therefore, the relationship between gradient and policy can be obtained by directly deriving the cumulative benefits, which determines the direction of the policy update. The process is as follows:

$$\nabla_{\theta} J(\theta) = E_{X_{\theta}}(\nabla_{\theta} \log \pi_{\theta}(s, a) r). \quad (16)$$

Considering the advantages of the value function optimization learning algorithm and the policy optimization learning algorithm, a framework for the actor-critical algorithm is proposed. In the verification learning algorithm based on the parameter  $\omega$  value function, the key part updates the time series difference method, and the formula is as follows:

$$Q_{\omega} = \omega + \partial(R_t + \gamma q(s, a) - Q_{\theta}(s, a_t)). \quad (17)$$

The Actor part evaluates the key parts of the current policy based on the parameters and uses the policy gradient statement of the policy-based validation learning algorithm to update the parameter  $\theta$ , the formula is as follows:

$$\theta = \theta + \partial \nabla \log \pi_{\theta}(s, a) Q_{\omega}(s_t, a_t). \quad (18)$$

**3.3. Deep Reinforcement Learning.** In principle, traditional reinforcement learning algorithms can solve most decision problems, but due to the complexity of algorithms and early computational power limitations, traditional reinforcement learning algorithms can often only solve decision problems

in a simple way. DQN is an iterative value learning algorithm derived from Q-learning algorithm, but combined with the deep learning method solves the dimension explosion problem of the Q-learning algorithm. The network structure is shown in Figure 2.

Since it is impossible to calculate the expected value of the Q value corresponding to each function in the actual execution, the method adopted by DQN is to select the maximum value of the Q value corresponding to each function to be learned and converge to the optimal value. After several iterations. This process can be summarized as follows: the learned Q value is the expected maximum Q value of each function, with the following proportion:

$$E(\max(Q_1, Q_2, \dots, Q_n)) \geq \max(E(Q_1), E(Q_2), \dots, E(Q_n)). \quad (19)$$

#### 3.4. Different-Strategy Reinforcement Learning.

Reinforcement learning with different strategies is a general term for a class of reinforcement learning algorithms, whose equivalent is reinforcement learning with the same strategy. The classification is based on whether the policy is the same when the policy interacts with the environment and when the policy is updated. The same policy reinforcement learning algorithms require the same policies and upgrade strategies as the environment interaction, while different reinforcement policy learning algorithms are different. It does not have to be the same strategy, the specific difference is:

$$\begin{aligned} Q(s_t, a_t) &\leftarrow \partial(r + \partial q_s \cdot q_a - \gamma(s, a)), \\ Q(s_t, a_t) &\leftarrow Q_s + \partial(r + \gamma \max_{a'} q_{a'} - q_a). \end{aligned} \quad (20)$$

The importance of using the absolute value of TD\_error to achieve better reaction sample data. The TD\_error is defined as follows:

$$\text{TD\_error} = r + \partial Q(s', a') - Q(s, a). \quad (21)$$

To enable faster policy convergence, sample data with higher absolute values of TD\_error are often learned more frequently. Therefore, the PER algorithm takes the absolute value of the TD\_error of each data as an indicator and samples the empirical pool data according to the value size. The sampling probability follows the following formula:

$$P(i) = \frac{P_i^a}{\sum_k P_k^a}. \quad (22)$$

The sampling weight is introduced to correct the deviation generated in the equation as follows:

$$w_i = \left( \frac{1}{N} \frac{1}{P(i)} \right)^{\beta}. \quad (23)$$

Learning different strategies is characterized by fast convergence speed and high sample utilization rate. The introduction of an empirical replication mechanism has the advantages of reducing the correlation of sample data and improving the algorithm robustness.

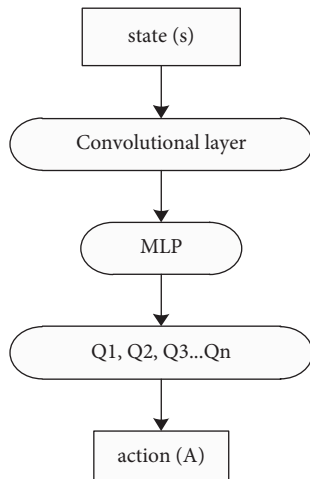


FIGURE 2: D Q N network structure.

## 4. An Empirical Study on Learning Strategy Training for English Learners

**4.1. Selection of Experimental Subjects.** Since we cannot disturb the normal teaching course in the learning process, we choose some “people who are not good at learning” to form the experimental class and the control class. The following two steps were performed for randomly selected classes: the first step is the single-sample *T*-test method, policy use level for each test category, and policy dominance for all subjects tested separately; the second step is the independent sample *t*-test for parameter test, the Mann-Whitney test for two independent samples, screening the policy usage status of all test categories, and determining the combinations of all test categories. There were no significant differences between the two strategies. Subsequently, the attitude of the experimental class and the control class to the strategy training was comprehensively studied. Specific statistical results are shown in Tables 1–3. The results of student comparison strategies between test and control classes are shown in Figure 3.

This can be seen from the test results in Figure 3 and Table 3. Under the condition of homogeneity of variance, the *T* value is 0.44, and the signal value (bilateral) is 0.965, much higher than the observation value of 0.05, indicating that there is no significant difference between the students in the use of English learning strategies. As can be seen from the statistical results of Tables 1–3 and Figure 3, the experimental class and control class selected in this study cannot only fully represent the parent class of this study, but also fully meet the same level. The strategies adopted and the qualitative requirements of the experimental study can ensure the authenticity and scientific nature of this study.

**4.2. Content of Strategy Training.** Cohen notes that “The goal of strategic education is to clearly teach students when, why, and how to use learning strategies to promote the learning and use of foreign languages.” The students are encouraged to learn foreign languages on their own, rather than always

relying on the teacher’s guidance. The strategy training has two purposes: one is to help students with poor English to identify 50 specific strategies to use the Oxford Learning Strategy Scale; and the other is to help them. Establish a certain strategic awareness, learn to learn English, with strategic knowledge to promote their own English learning.

This strategy training takes the experimental students’ strategy application level as the main reference. In terms of course content and contacts, fully considering the characteristics of researchers’ strategy application, and carries out special lectures, mutual aid groups, theme activities, and strategy training activities.

### 4.3. Training and Analysis of English Learning Strategies.

After the experiment, we made the longitudinal comparison of the experimental class students from the following seven aspects in Figure 4, and the difference significance test is shown in Table 4, aiming to determine the influence of strategy education on the level of strategy use in the experimental classroom. The proportions in Table 4 represent the 1-year English learning strategy training. The students in the experimental class showed no difference in the use of strategies such as memory, cognition, compensation, metacognition, emotion, and social interaction, and the proportion of each item is measured as a sample of a separate population, so the proportions are not correlated with each other.

The above statistics show that after a year of English learning strategy training, the students in the experimental class have no difference in the use level of memory, cognition, compensation, metacognition, emotion, social interaction, and other strategies. The overall strategy showed a clear upward trend, with statistically significant differences at 0.01, and the biggest improvement was social strategies, followed by metacognitive strategies. It can be seen that the level of the strategy application has improved after the strategy utilization rate of the experimental class after strategy training.

To test the effectiveness of strategy training in managing changes in student strategy use levels, we performed longitudinal comparisons of strategy use levels between control students before and after testing in Figure 5 and difference dominance tests in Table 5. From Figure 5 above, it can be seen that the difference before and after the experiment is not more than 0.1, and there is basically no change. Although the use of cognitive, emotional, and social strategies has improved, the improvement of cognitive and social strategies is not significant.

The statistical results in Table 5 showed that the use of six-dimensional and general strategies before and after the experiment were covered by “universal use,” and the levels of memory, compensation, and metacognitive strategies used by the control group were 0.07828, 0.09848, and 0.06566 before and after the experiment, respectively. It can be seen that the difference before and after the experiment is not greater than 0.1, meaning that there is no change in principle. Furthermore, while cognitive, emotional, and social strategy use improved, cognitive and social strategies were

TABLE 1: Homogeneity test of the level of English learning strategies used in the experimental classes.

Single sample <i>T</i> test				
Test value = 2.66	<i>t</i>	df	Sig (bilateral)	Mean difference
Policy average	-0.298	44	0.767	-0.01556

TABLE 2: Homogeneity test of the use level of English learning strategies in the control class.

Single sample <i>T</i> test				
Test value = 2.66	<i>t</i>	df	Sig.(bilateral)	Mean difference
Policy average	-0.307	43	0.760	-0.019

TABLE 3: Test of significance in the level of strategy use between experimental and control classes.

	The Levene's test for the variance equation				A <i>t</i> -test for the mean equation	
	<i>F</i>	Sig	<i>T</i>	df	Mean variance	Standard error value
Variance is equal	0.154	0.696	0.44	87	0.00354	0.08093
Variance is unequal	0.155	0.567	0.44	84.11	0.00354	0.08108

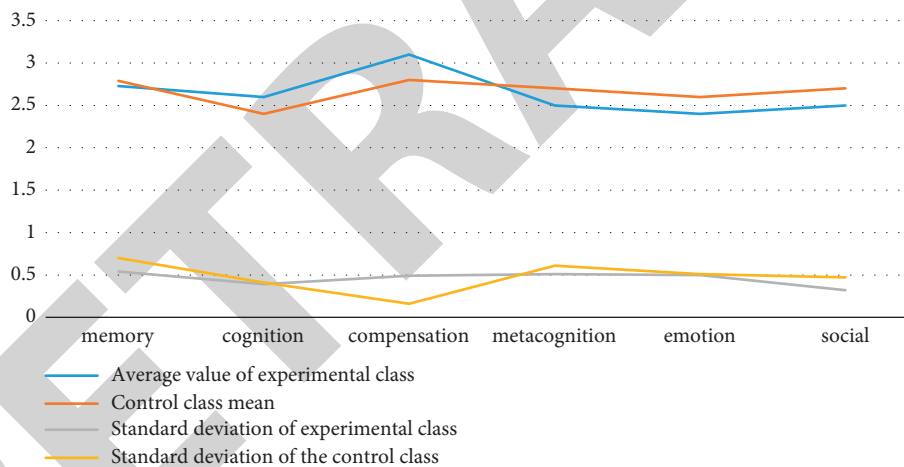


FIGURE 3: Comparison of student strategy usage performance between the two classes.

not significant and the change was not statistically significant, but there was a 0.31 percentage point difference in emotional strategy use before and after the experiment, which reached a statistically significant difference.

After the strategy practice, students in the test and control classes were compared laterally as shown in Figure 6 and an explicit difference test according to Table 6 to assess whether student utilization in the test class should be higher than students.

Statistics in Table 6 show that after the exam, the experimental grade students not only in memory strategy and

overall strategy is better than the reference class, and all the differences reached the statistical level, the biggest difference is social strategy, on average of 1.01 points, followed by cognitive strategy and metacognitive strategy, differ more than 0.80 points. Furthermore, although affective and memory strategies were minimal, the difference was also greater than 0.50 points.

**4.4. Strategy Training Results.** First, from the macroscopic perspective of the strategy use level, the horizontal

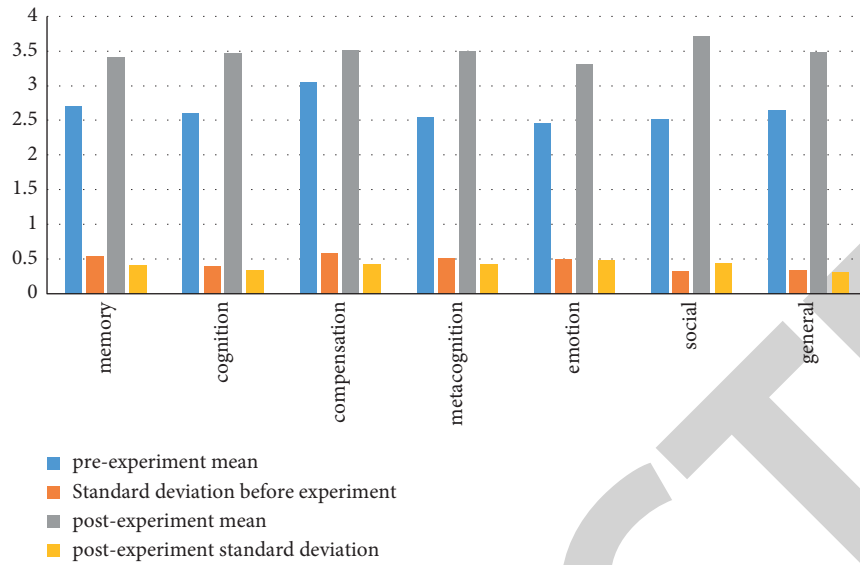


FIGURE 4: Comparison of the use effect of student learning strategies in the experimental class before and after the experiment.

TABLE 4: Results of the significance test for the differences in the experimental class.

	T price	Sig.(bilateral)
Memory strategy	-6.712	0.000
Cognitive strategy	-11.017	0.000
Compensation strategy	-4.182	0.000
Metacognitive strategy	-9.612	0.000
Emotional strategy	-8.152	0.000
Social strategy	-14.795	0.000
Total strategy	-11.971	0.000

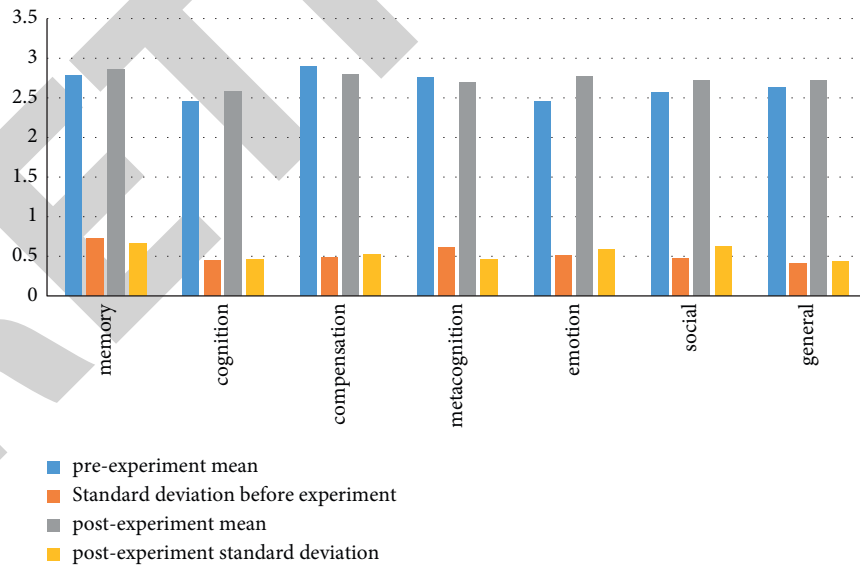


FIGURE 5: Comparison of the effects of learning strategies in the control class students before and after the experiment.

comparison difference of the experimental grade strategy use level before and after the experiment was 0.84 and 0.76 points, respectively. The level of strategy use of experimental and control students can prove that strategy training does improve the level of strategy use of learners,

and the impact is very significant. The use of these four strategies has changed from a general level to a common postexperimental level, where English learning strategy training effectively improves the use of strategies by poor learners.



TABLE 5: Results of the significance test for the difference in the control class.

	T price	Sig (bilateral)
Memory strategy	-5.38	0.592
Cognitive strategy	-1.33	0.187
Compensation strategy	0.905	0.368
Metacognitive strategy	0.566	0.573
Emotional strategy	-2.638	0.010
Social strategy	-1.176	0.243
Total strategy	-0.870	0.387

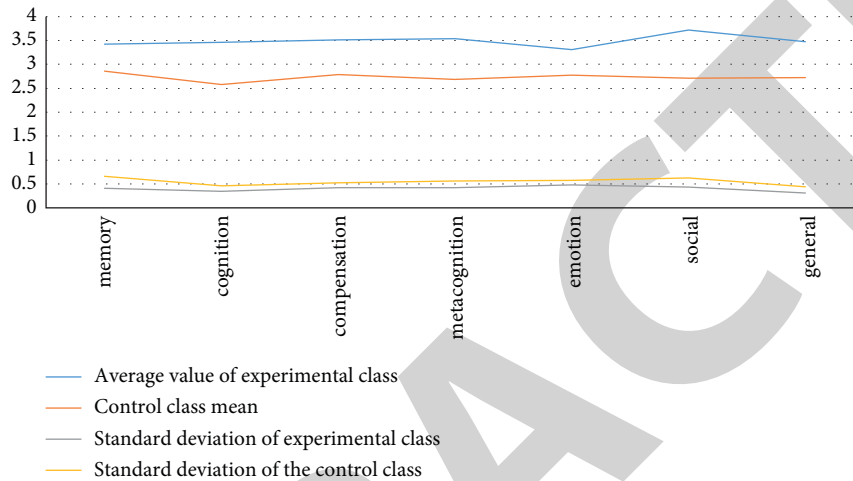


FIGURE 6: Comparison of the use effect of student learning strategies in the two classes after the experiment.

TABLE 6: Results of the significance test for the difference between the experimental class and the control class after the experiment.

	Experimental class-control class	T price	Sig (bilateral)
Memory strategy	0.5561	4.736	0.000
Cognitive strategy	0.8758	10.15	0.000
Compensation strategy	0.7194	7.16	0.000
Metacognitive strategy	0.8017	8.495	0.000
Emotional strategy	0.5412	4.747	0.000
Social strategy	1.138	8.799	0.000
Total strategy	0.7627	9.428	0.000

Finally, from the microperspective of the change of the use strategy level of students in the experimental class, the utilization rate of 50 strategies in the student experimental class showed that 42 out of 50 strategies showed more than 0.50, that is, 84% of the total strategies, and can reach the normal level. At the operational level, there are as many as 25 strategic products, accounting for 50% of the total strategy. The above data fully show that in the whole system of this strategy training, the experimental activities of strategy training have produced a synergistic effect, which has greatly promoted the application of other strategies among disciplines, and they have a strong sense of strategy, which has proved the success and success of this strategy training.

## 5. Conclusion

At present, the research on multimodal English learning strategy based on computational intelligence is finally

completed, we first use the Oxford language learning strategy questionnaire as the main research tool, examined the strategy use status of 464 poor English students, widely revealed the characteristics of poor English students strategy use, and discussed the influence on their strategy formation. The level of strategy use itself, faculty, and external factors demonstrate the need and feasibility of implementing strategy training for researchers with completely poor English. It finds the factual basis for the selection of this strategic training content. Next, the results suggest that while the proportion of poorer college English researchers using the strategy is moderate, they use a wide range of strategies and have no clear preference for using it. The English learning strategy training not only improves the use level of the subject strategy but also improves greatly. In addition, the learning strategy training also effectively improves the English learning level of the students in the experimental class. First of all, the content of the survey and interview is

not comprehensive enough, and the persuasiveness of the research is still slightly insufficient. The research on multimodal English learning strategies based on computational intelligence has finally been completed. The level of strategy use itself, teachers, and external factors lies in the implementation of strategy training, necessity and feasibility. Although poor college English researchers use this strategy in a moderate proportion, they use a wide range of strategies and do not have a clear preference for using this strategy, which may not fully reflect the problems of multimedia courseware in the application of English subjects, and second, since listening, speaking, reading, writing and writing are mutually reinforcing and influencing each other, the application of intelligent multimodal English learning strategies in each teaching method is inevitably affected by other factors, which are ignored in this survey. The number of classes observed by the observation method is too small, and the representativeness of the observed classes is not strong.

### Data Availability

The experimental data used to support the findings of this study are available from the corresponding author upon request.

### Conflicts of Interest

The authors declare that they have no conflicts of interest regarding this work.

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