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iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 16 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i16.42707

PAPER

Personalizing Students' Learning Needs by a Teaching Decision Optimization Method

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ABSTRACT

With the rapid development of educational technology and the deepening of educational system reform, personalized education has gradually become an important topic in education. However, existing classroom teaching decision-making methods often fail to meet students' personalized learning needs, resulting in some students being unable to reach their full potential in the classroom. To solve this problem, this study proposed a multi-conditional factor classroom teaching decision optimization method based on the improved particle swarm optimization (IPSO) algorithm, and predicted students' personalized learning needs by combining with the improved ant colony optimization-support vector regression (IACO-SVR) model. First, the IACO-SVR model was used to collect students' learning data, such as grades, interests, hobbies and learning progress, to accurately predict their needs in different teaching contexts. Second, the IPSO algorithm was used to optimize the multi-conditional factor classroom teaching decisions, thus meeting the personalized needs of students. The IPSO algorithm had strong global search ability, which effectively found the optimal solution to achieve personalized teaching strategies. It is expected that the teaching quality can be improved by predicting the personalized learning needs of students and optimizing classroom teaching decisions in this study, thus providing better support for their comprehensive development. In addition, the results of this study can provide theoretical basis and reference for administrative departments of education and schools to formulate personalized education policies.

KEYWORDS

personalized learning needs of students, classroom teaching decisions, improved particle swarm optimization algorithm, support vector regression, ant colony optimization algorithm

1 INTRODUCTION

With the rapid development of educational technology and the advancement of educational system reform, people have higher requirements for education quality and fairness and students' all-round development [1–3]. Therefore, as an educational model focusing on students' differences and meeting their personalized learning

Zhang, Y., Shi, Y., Bi, F. (2023). Personalizing Students' Learning Needs by a Teaching Decision Optimization Method. *International Journal of Emerging Technologies in Learning (iJET)*, 18(16), pp. 222–236. https://doi.org/10.3991/ijet.v18i16.42707

Article submitted 2023-05-02. Resubmitted 2023-06-27. Final acceptance 2023-06-28. Final version published as submitted by the authors.

needs, personalized education has gradually become a hot topic in education [4–6]. As the main venue for cultivating students, classroom teaching is of crucial importance for realizing personalized education in this context [7–13].

However, existing classroom teaching decision-making methods often fail to meet students' personalized learning needs, resulting in some students being unable to reach their full potential in the classroom [14–17]. It is difficult for those traditional methods to fully consider the personalized needs of students, because their teaching design mainly relies on the teaching syllabus and the personal experience of teachers [18–21]. In this situation, the teaching contents and methods are often not diversified, which is not conducive to stimulating students' interests and initiative in learning. Moreover, the existing methods often regard students as a whole, ignoring their differences in knowledge acquisition, learning interests and progress, etc., which leads to some students having difficulty keeping up with the teaching progress or feeling bored during the teaching process, thus affecting their learning effect.

Therefore, to improve teaching quality and meet students' personalized learning needs, it is necessary to improve and optimize existing classroom teaching decision-making methods. This research aimed to study the optimization method of multi-conditional factor classroom teaching decisions, thus addressing the shortcomings of existing methods, and providing support for achieving personalized education.

The IACO-SVR model combines the improved ant colony optimization (IACO) algorithm with support vector regression (SVR) to predict students' personalized learning needs. By collecting students' learning data, such as grades, interests, hobbies, and learning progress, the IACO-SVR model can accurately predict students' needs in different teaching contexts, providing a basis for teachers to develop personalized teaching strategies.

On the basis of predicting students' personalized learning needs, this research took English teaching as an example to study the multi-conditional factor classroom teaching decision optimization based on the IPSO algorithm. Particle swarm optimization (PSO) algorithm is an intelligent optimization algorithm with strong global search ability. By improving the PSO algorithm, the multi-conditional factor classroom teaching decisions were optimized, which fully met the personalized needs of students.

This study aimed to propose a more effective classroom teaching decision-making method, thus helping teachers design and implement teaching tailored to students' personalized learning needs. It is expected that teaching quality can be improved by predicting the personalized learning needs and optimizing classroom teaching decisions, thus providing better support for students' comprehensive development. In addition, the results of this study can provide theoretical basis and reference for administrative departments of education and schools to formulate personalized education policies.

2 PREDICTING THE PERSONALIZED LEARNING NEEDS OF STUDENTS

In the classroom teaching decision optimization context oriented towards students' personalized learning needs, a multi-conditional factor model predicting those needs was constructed in this study, mainly because classroom teaching conditional factors changed along with the changes in teaching contents and methods, and students' needs in the actual teaching process, which directly affected their learning needs. However, traditional teaching decision-making methods often overlook the impact of multi-conditional factors on students' personalized learning needs, resulting in teaching decisions hardly meeting their personalized needs. The constructed model reflected the impact of changes in classroom teaching conditional factors on the personalized learning needs.

When making regulatory decisions on classroom teaching conditional factors, students' personalized learning need information was referred to. The SVR algorithm was used in the model, which solved the multi-variable nonlinear regression problem very well with a high prediction accuracy. The IACO algorithm optimized the parameters of the SVR model, which improved the stability and accuracy of the prediction model.

2.1 Relational table of students' personalized learning needs and classroom teaching conditional factors

Based on the similarity of data sequences, the grey relation analysis (GRA) method was not limited by the number of historical samples and sample patterns, and was suitable for dealing with small samples, nonlinear and uncertain problems. GRA effectively reduced the algorithm complexity in computation time and space, and well determined the classroom teaching conditional factor variables highly correlated with students' personalized learning needs, which was consistent with common data characteristics in educational scenarios. Figure 1 shows a certainty/uncertainty analysis schematic diagram of the classroom teaching decision-making process. This method was used to evaluate the degree of students' personalized learning needs affected by various classroom teaching conditional factors, which helped teachers understand the importance of each factor, thus developing more effective teaching strategies.

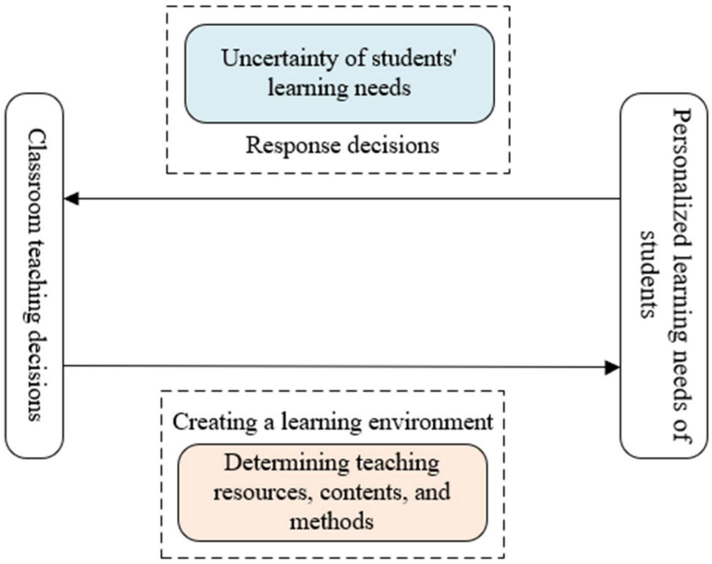

Fig. 1. Certainty/uncertainty analysis of classroom teaching decision-making process

Steps of the GRA method were introduced in detail as follows:

Let the standard data array $T = \{T(b)\}$ be students' personalized learning needs, the correlation data array $Z_u = \{Z(b)\}(u = 1, 2, \ldots, l)$ be the classroom teaching conditional factors that may affect the output of those needs, $\Delta u(b) = |T(b) - Z_u(b)|$, and η be the identification coefficient ranging between [0, 1]. The closer η to 0, the greater the identification ability. The closer η to 1, the smaller the identification ability. Calculation formula of the correlation coefficient ζ_u of the two data arrays was given as follows:

$$\varsigma_u(b) = \frac{\underset{u}{MIN}\,\underset{b}{MIN}\,\Delta u(b) + \eta \underset{u}{MAX}\,\underset{b}{MAX}\,\Delta u(b)}{\Delta u(b) + \eta \underset{u}{MAX}\,\underset{b}{MAX}\,\Delta u(b)} \tag{1}$$

Let e_u be the correlation value between the standard and correlation data arrays, then calculation formula of the correlation was given as follows:

$$e_u = \frac{1}{J}\sum_{b=1}^{J}\zeta_u(b) \tag{2}$$

2.2 Constructing a model predicting students' personalized learning needs

Students' classroom learning process was mainly divided into three stages, namely, preparation stage, exploration stage, and consolidation stage. According to the previous analysis, students had different learning needs at different learning stages. Therefore, by utilizing their personalized needs at three different classroom stages and corresponding classroom teaching conditional factor dataset, a full classroom stage IACO-SVR prediction model was constructed to accurately predict students' personalized learning needs. The constructed model had high prediction accuracy and stability, which effectively predicted the personalized needs of students at various stages. By analyzing the relationship between the personalized learning needs at different stages and classroom teaching conditional factors, teachers adjusted teaching strategies more effectively to improve the teaching quality.

The specific steps were as follows:

(1) The GRA algorithm was used to obtain the correlation between each classroom teaching conditional factor and students' personalized learning needs. The factors with high correlation and corresponding personalized learning needs were selected to form the sample data of the model, which quantitatively described the development and changes of the factor variables and the personalized learning needs.

(2) Data in several aspects was collected, such as personalized learning needs of students in the English classroom, classroom teaching conditional factors, basic information of students, and other data that may affect the personalized learning needs, which was pre-processed, including data cleansing, standardization and coding, as well as feature selection. Then the dataset was usually divided into a training set and a testing set through random sampling, with the training set accounting for 70% to 80% of the dataset and the testing set accounting for the remaining 20% to 30%. The training set was used to train the model, and the testing set was used to evaluate the model's generalization ability. Data distribution in both sets was similar to avoid model overfitting or underfitting.

(3) The IACO algorithm was used to optimize the three key SVR parameters, namely, penalty parameter, kernel function parameter, and slack variable. An initial solution was randomly generated for each ant in the parameter search space, i.e. a set of values for the three key parameters. The current solution of each ant was substituted into the SVR model and was trained using training data, which aimed to calculate the prediction error of the model on the validation set to evaluate the fitness value. Then each ant was moved to the position with a new solution, i.e. the new values of the penalty parameter, kernel function parameter, and slack variable. Among all the solutions found by the ants, the solution with the highest fitness value was selected, i.e. a combination of the optimal penalty parameter, kernel function parameter, and slack variable, which was used to construct the SVR prediction model. The model was trained using training data, and its performance was evaluated on the testing set.

(4) A model based on the IACO-SVR algorithm was constructed to predict the personalized learning needs of students. The IACO algorithm was used to optimize the key parameters of SVR. As a regression model, SVR was used to predict students' personalized learning needs. The IACO algorithm improved the prediction accuracy of the SVR model by finding the optimal parameter combination. Then SVR was used to train the model, and the output values were denormalized, which obtained the predicted results. When the above steps were performed for the three-stage classroom learning dataset, the full classroom stage model predicting students' personalized learning needs was completed.

Based on the classic radial basis function, the function relationship between the input z_k and the output Oe was described as follows:

$$Oe = \sum_{u=1}^{m} (\beta_u - \beta_u^*) \exp\left(\frac{-\left\| z_u - z_k \right\|}{2\delta^2} \right) + n \tag{3}$$

3 MULTI-CONDITIONAL FACTOR CLASSROOM TEACHING DECISION OPTIMIZATION

A greenhouse classroom teaching conditional factor optimization model was constructed based on the IPSO algorithm. With the students' personalized learning need prediction IACO-SVR model as the fitness function, the IPSO algorithm was used to solve the classroom teaching conditional factor combination with the maximum fitness function, which obtained the optimal solution for interest and understanding level under the classroom teaching conditional factor coupling condition at different teaching stages, which maximized the personalized learning needs of students as crops. The classroom teaching decision optimization model with two conditional factors (interest and understanding level) was studied based on the IPSO algorithm. Figure 2 shows the regulatory decision-making process of the factors based on IACO-SVR.

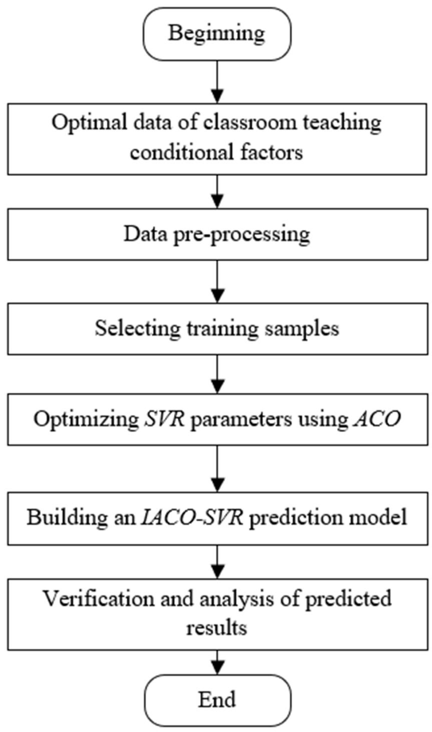

Fig. 2. Regulatory decision-making process of classroom teaching conditional factors based on IACO-SVR

3.1 IPSO algorithm

For the classroom teaching decision optimization oriented towards students' personalized learning needs, the optimal solution needed to be found in the multi-dimensional solution space. The standard PSO algorithm may fall into the local optimal solution, resulting in problems, such as too fast or slow convergence rate, a low optimization accuracy and so on. Optimized and improved PSO algorithm dynamically adjusted parameters without compromising the convergence characteristics of the algorithm, which improved the optimization performance, thus making the optimization results more reliable and authentic. With interest and understanding level as important factors affecting students' personalized learning needs, the PSO algorithm was optimized and improved and was then applied to the classroom teaching decision optimization with two conditional factors (interest and understanding level), which adaptively adjusted optimization strategies according to the problem characteristics at different stages, thus improving the optimization efficiency and accuracy.

The k-dimensional component O_{uk}^{j} of the optimal value of the u-th particle was replaced with the average value of the particle, and then the core updating formula for the particle's position and velocity in each movement was rewritten. Let O_{AV}^{j} be the average value of the optimal positions passed by B particles in the j-th iteration population, then the new formulas were given as follows:

$$c_{uk}^{j+1} = qc_{uk}^{j+1} + v_1 e_1 (o_{AV}^{j} - z_{uk}^{j}) + v_2 e_2 (o_{hk}^{j} - z_{uk}^{j}) \tag{4}$$

$$o_{AV}^{j} = \frac{(o_{1k}^{j} + o_{2k}^{j} + \ldots + o_{Bk}^{j})}{B} \tag{5}$$

When the inertia weight μ was adjusted to an adaptive change state based on particle fitness values, then there were:

$$\mu = \begin{cases} \mu_{MI} - \dfrac{(\mu_{MA} - \mu_{MI})(h - h_{MI})}{h_{AV} - h_{MI}}, & h \geq GA \\ \mu_{MA}, & h < GA \end{cases} \tag{6}$$

Similarly, when the accelerated factor was adjusted to a dynamic variation, then there were:

$$v_1(j) = v_{1a} + \left(v_{1r} - v_{1a}\right)\cos\left(\frac{\pi j}{2Y}\right) \tag{7}$$

$$v_2(j) = v_{2a} + (v_{2r} - v_{2a})\sin\left(\frac{\pi j}{2Y}\right) \tag{8}$$

3.2 Constructing the interest level target value optimization model

Interest level played a very important role in students' classroom learning engagement. The IPSO-based optimization model oriented towards students' interest level was established in the following specific steps:

(1) Building optimization combination conditions. Each optimization of the algorithm was carried out under certain dynamic optimization combination impact factor conditions. Based on the range of various classroom teaching conditional factors adapted to by students, different categories of changes were made to the three dynamic conditional factors, namely, teaching resources, contents, and methods, in order to construct the optimization combination conditions.

A sample dataset $Z_Y^u = (Z_Y^1, Z_Y^2, \ldots, Z_Y^7)$ of teaching resource conditions was established, which consisted of seven teaching resource categories, namely, textbooks and reference books, multimedia resources, digital resources and online platforms, physical models and experimental equipment, teaching aids, learning activity materials, evaluation and feedback tools. A sample dataset $Z_G^k = (Z_G^1, Z_G^2, \ldots, Z_G^7)$ of teaching content conditions was formed, which consisted of five teaching content categories, namely, knowledge-based and skill-based contents, emotional attitudes, values, and learning strategies. A sample dataset $Z_O^u = (Z_O^1, Z_O^2, \ldots, Z_O^7)$ of teaching methods was formed, which consisted of nine teaching method categories, namely, teaching, question-and-answer method, case study, group cooperative learning, project-based learning, role play, flipped classroom, microlecture, and blended learning. Teaching resources, contents and methods were instantiated for subsequent completion of the optimization model.

(2) Determining the fitness function of the optimization algorithm. After calling the formula of the personalized learning need prediction IACO-SVR model, the above classroom teaching conditional factor optimization combination conditions were substituted into the prediction model, which obtained the prediction function relationship regarding the instantiated classroom teaching conditional factors.

$$\begin{aligned} Oe_{ukj} &= d(Z_Y^u, Z_G^k, Z_O^j, Z_V) = \mu \cdot \theta(Z_Y^u, Z_G^k, Z_O^j, Z_V) + n \\ &= \sum_{b=1}^{m} \left(s_b - s_b^*\right) \exp\left(- \frac{\left\| Z_b - \left(Z_Y^u, Z_G^k, Z_O^j, Z_V\right) \right\|}{2\delta^2} \right) + n \end{aligned} \tag{9}$$

Let Z_V be the interest level target value, and $FIT(Z_V)$ be the fitness function, i.e., the interest level variable function under the combination conditions of teaching resources and contents and understanding level. The PSO-based fitness function expression for the target value optimization was as follows:

$$FIT_{ukj}(Z_V) = d(Z_Y^u, Z_G^k, Z_O^j, Z_V) \tag{10}$$

(3) IPSO-based target value optimization. The students' personalized learning need prediction function was first selected as the fitness function of the IPSO algorithm. After a set of classroom teaching conditional factors of teaching resources, contents and methods were determined, the algorithm parameters were set and initialized, such as the number and size of initialized particle swarms, the maximum number of iterations, initial positions and velocities of particles.

The fitness corresponding to the position of each particle was further calculated. Particle positions and velocities were updated based on the revised inertia weight and accelerated factor of the algorithm. Iterative optimization ensured that the individual and global optimal values of the population moved towards the global optimal solution. The algorithm stopped iteration when the optimal solution under the current classroom teaching conditional factor condition combination was found.

3.3 Constructing the understanding level target value optimization model

Understanding level was the foundation for students to continuously engage in classroom learning, and was also one of the factors affecting students' classroom learning effect. A low understanding level made students feel that the current teaching resources, contents and methods were not matched or suitable, which reduced their personalized learning needs, and prevented them from further learning, especially at the classroom learning exploration stage. The understanding level reflected the maximum ability of students to complete classroom learning tasks, and had a strong correlation coupling relationship with teaching resources, contents and methods. Similarly, an understanding level target value optimization model was constructed in this study. To make greenhouse lighting classroom teaching conditional factors achieve suitable growth conditions for tomatoes, it was necessary to first obtain the time saturation point maximizing the personalized learning needs of students as tomatoes under different greenhouse classroom teaching conditional factor combination conditions. The IPSO-based understanding level optimization model was built using the following critical steps:

(1) Building optimization combination conditions. Similar to Section 2.2, different categories of changes were made to the three dynamic classroom teaching conditional factors to construct optimization combination conditions.

(2) Selecting the fitness function of the optimization algorithm. According to Formula 1 in Chapter 2, the relational expression of the students' personalized learning need prediction function concerning the instantiated classroom teaching conditional factors was obtained as follows:

$$\begin{aligned} Oe_{ukj} &= d(Z_Y^u, Z_G^k, Z_V^l, Z_O) = \mu \cdot \theta(Z_Y^u, Z_G^k, Z_V^l, Z_O) + n \\ &= \sum_{b=1}^{m} \left(s_b - s_b^*\right) \exp\left(-\frac{\left\| Z_b - (Z_Y^u, Z_G^k, Z_V^l, Z_O) \right\|}{2\delta^2}\right) + n \end{aligned} \tag{11}$$

Let Z_O be the understanding level target value, then the fitness function expression of target value optimization using PSO was given as follows:

$$FIT_{ukj}(Z_O) = d(Z_Y^u, Z_G^k, Z_V^l, Z_O) \tag{12}$$

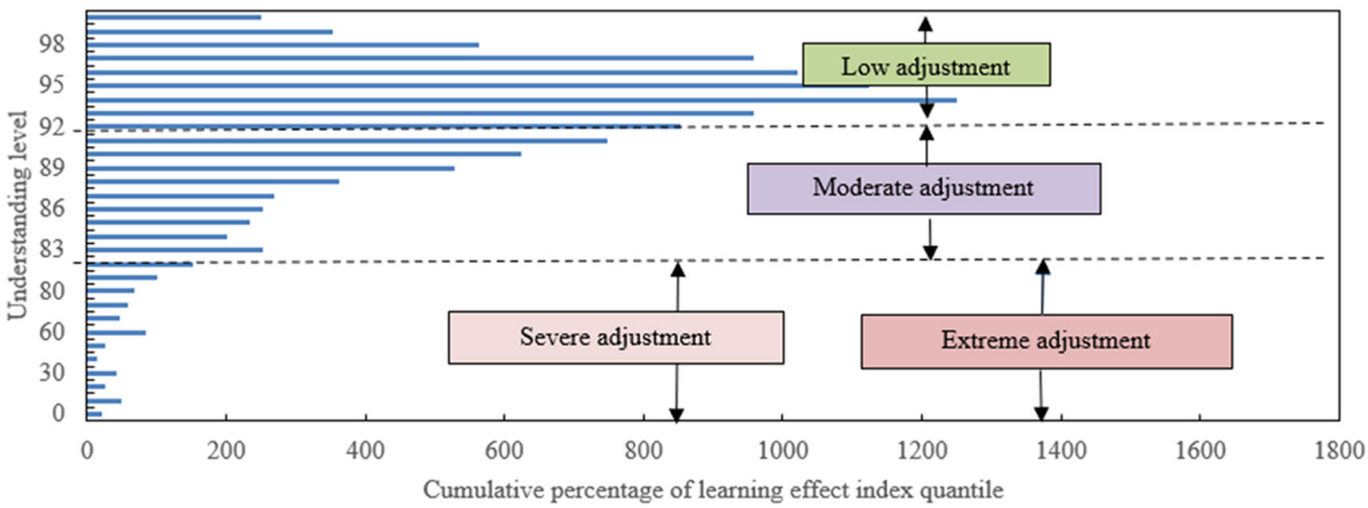

Fig. 3. Histogram of understanding level distribution and schematic diagram of selecting teaching decision adjustment criteria

Figure 3 shows the histogram of understanding level distribution and the schematic diagram of selecting teaching decision adjustment criteria. Based on Figure 3, the classroom teaching decision-making plans can be adjusted according to the understanding level.

4 EXPERIMENTAL RESULTS AND ANALYSIS

Table 1. GRA results

Conditional Factors	Interest Level	Understanding Level	Teaching Resources	Teaching Contents	Teaching Methods	Learning Effect
Preparation stage	0.715	0.538	0.451	0.562	0.619	0.857
Exploration stage	0.739	0.504	0.362	0.597	0.685	0.813
Consolidation stage	0.627	0.596	0.481	0.525	0.637	0.859

Table 1 shows the GRA results of various conditional factors at the preparation, exploration and consolidation stages. It can be seen from the table that the relational degrees of interest and understanding level, teaching resources, contents and methods at the preparation stage are 0.715, 0.538, 0.451, 0.562, and 0.619, respectively, indicating that interest level has the greatest impact on learning effect at the preparation stage, followed by teaching methods, with understanding level and teaching contents having certain impact, while the impact of teaching resources is relatively small. The relational degrees of the factors at the exploration stage are 0.739, 0.504, 0.362, 0.597, and 0.685, respectively, indicating that interest level is still the most important factor affecting learning effect at the exploration stage, and the impact of teaching methods is also significant. Compared with the preparation stage, the impact of understanding level, teaching contents and resources is smaller. The relational degrees of the factors at the consolidation stage are 0.627, 0.596, 0.481, 0.525, and 0.637, respectively, indicating that teaching methods have the greatest impact on learning effect at the consolidation stage, followed by interest and understanding level. Compared with the first two stages, the impact of teaching resources and contents gradually increases. The GRA results show that interest level and teaching methods have a significant impact on learning effect at different teaching stages, especially at the preparation and exploration stages. Therefore, when designing teaching activities, teachers should improve the learning effect by focusing on increasing students' interest level and adopting effective teaching methods. Although understanding level had varying impacts on learning effect at different stages, it was still an important factor on the whole. Teachers should pay attention to students' understanding level and take corresponding measures to help them improve their understanding level.

To verify the effectiveness of the classroom learning interest level IACO-SVR model at the preparation stage, the model was validated in this study. The fitting and prediction results of actual data showed that the fitting curve given by the IACO-SVR model fit the value of students' classroom learning interest level to a high degree, indicating that the IACO-SVR model was highly accurate and reliable in analyzing and predicting students' classroom learning interest level, thus providing strong support for teachers to develop effective teaching strategies at the preparation stage (Figure 4).

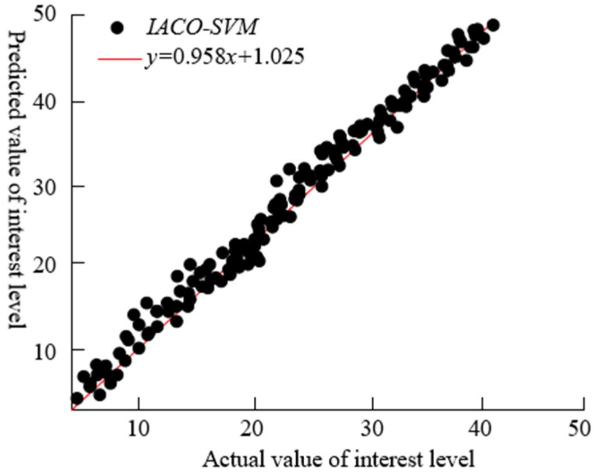

Fig. 4. Validation of the students' classroom learning interest level IACO-SVR model at the preparation stage

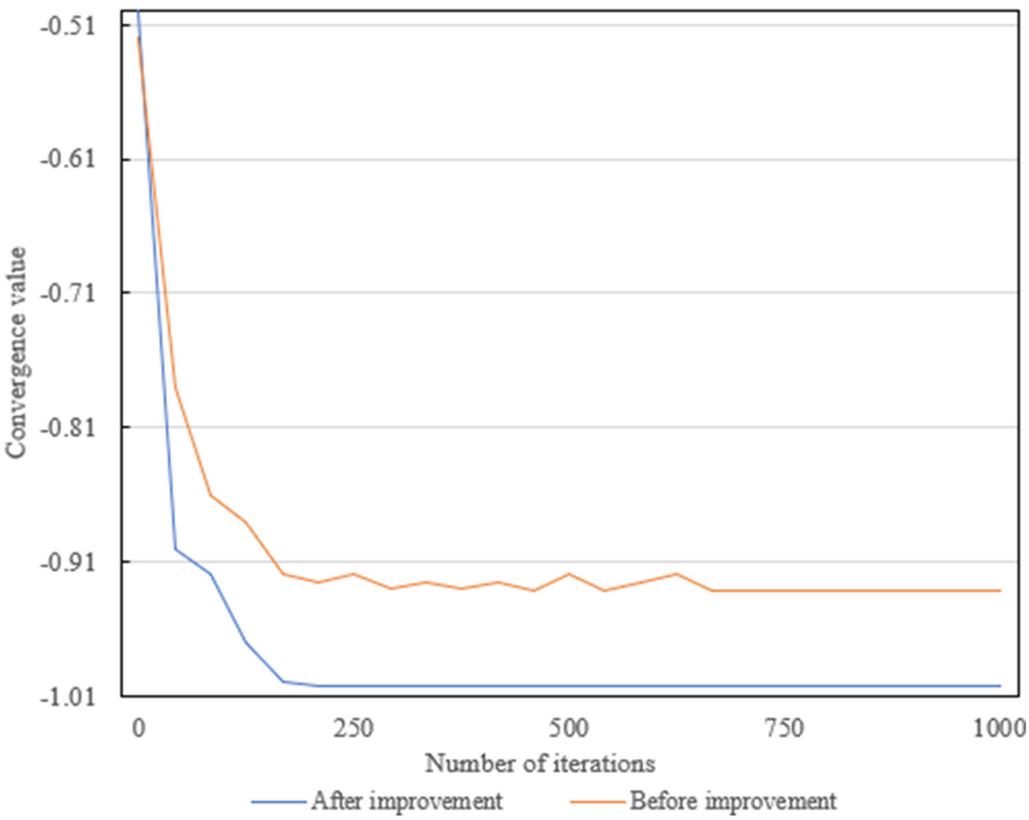

Fig. 5. Optimization comparison before and after algorithm improvement

Figure 5 shows the optimization comparison before and after the PSO improvement in the classroom teaching decision optimization scenario oriented towards students' personalized learning needs. The figure lists the optimization values before and after the PSO improvement with different numbers of iterations (e.g. 0, 250, 500, 750, and 1,000). As shown in the figure, the improved optimization value is slightly lower than the value before improvement at the initial iteration stage (with 0 iteration), indicating that the IPSO algorithm may take some time to adapt to the search space at the beginning of optimization. As the number of iterations increases, the improved optimization value gradually decreases, demonstrating better optimization performance. When the number of iterations reaches 250, the improved optimization value is significantly better than the value before improvement, and this advantage is maintained in the subsequent iteration process. When the number of iterations reaches 1000, the improved optimization value is significantly lower than the value before improvement, indicating that the IPSO algorithm has stronger global optimization ability and can better find the global optimal solution. In summary, in the classroom teaching decision optimization context oriented towards students' personalized learning needs, the IPSO algorithm had significantly better optimization performance than the PSO algorithm, meaning that the IPSO algorithm more effectively met the personalized learning needs of students, thus providing better support for teachers to make appropriate teaching decisions at different teaching stages.

Table 2. Evaluation index results of the model before and after improvement

Evaluation Indexes	Preparation Stage		Exploration Stage		Consolidation Stage	
	After Optimization	Before Optimization	After Optimization	Before Optimization	After Optimization	Before Optimization
MAE	0.625	1.352	0.715	1.352	0.751	1.258
MSE	0.847	3.627	0.836	3.296	0.936	2.691
RMSE	0.915	1.025	0.914	1.384	0.915	1.527
R^2	0.936	0.967	0.926	0.958	0.968	0.942
Pearson	0.951	0.915	0.918	0.901	0.947	0.963

Table 2 shows the evaluation index results of the multi-conditional factor classroom teaching decision optimization model before and after the PSO algorithm improvement in the classroom teaching decision optimization scenario oriented towards students' personalized learning needs. The indexes include mean absolute error (MAE), mean square error (MSE), root mean square error (RMSE), determination coefficient (R^2), and Pearson correlation coefficient (Pearson). It can be seen from the table that the optimized model performs better than the model before optimization in terms of MAE, MSE, and RMSE at the preparation, exploration and consolidation stages, meaning that the IPSO algorithm predicts the classroom teaching decisions more accurately with smaller errors. In terms of R^2 index, the optimized model performs slightly lower than the model before optimization at the preparation and exploration stages, but outperforms that at the consolidation stage. Despite some fluctuations, the optimized model still performs well in explaining the target variables on the whole. As for the Pearson index, the optimized model performs better than the model before optimization at the preparation and consolidation stages, but performs slightly lower than that at the exploration stage, indicating that the IPSO algorithm has a stronger correlation with actual results with better prediction ability at the preparation and consolidation stages. In summary, the multi-conditional factor classroom teaching decision optimization model optimized by the PSO algorithm improved its overall performance at the preparation, exploration and consolidation stages compared with the model before optimization, indicating that the IPSO algorithm more effectively met the personalized learning needs of students, thus providing more accurate support for teachers to make appropriate teaching decisions at different teaching stages.

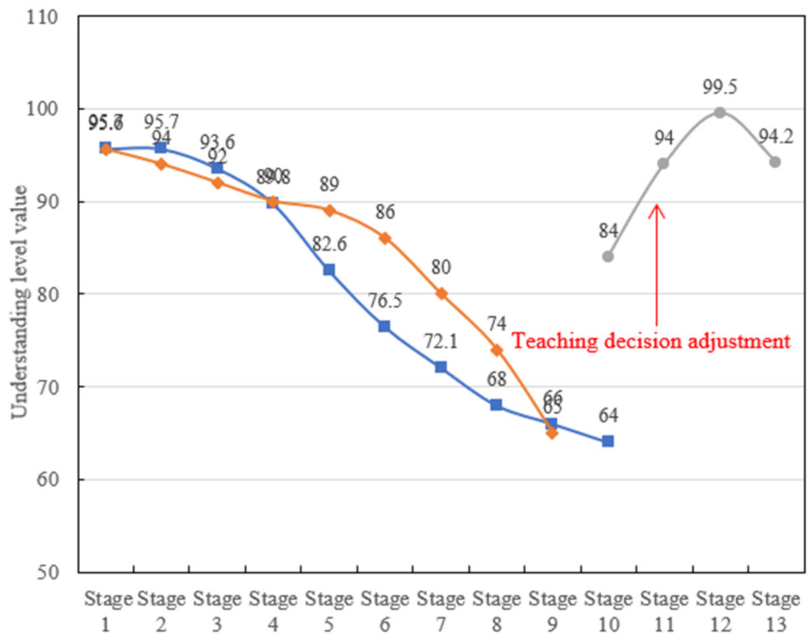

Fig. 6. Changes of students' understanding level before and after teaching decision adjustment

Figure 6 shows the changes of students' understanding level before and after teaching decision adjustment in the classroom teaching decision optimization scenario oriented towards personalized learning needs of students. As shown in the figure, the predicted value of students' understanding level gradually decreases from 95.7 at Stage 1 to 64 at Stage 9 before teaching decision adjustment, while the actual value also gradually decreases from 95.6 at Stage 1 to 65 at Stage 9, indicating a decrease in students' understanding level during the teaching process, possibly due to factors such as teaching methods and contents, or personalized learning needs of students. After the teaching decision adjustment, students' understanding level value significantly improves from 84 at Stage 10 to 94 at Stage 11 and then to 99.5 at Stage 12, but slightly decreases to 94.2 at Stage 13, indicating that the adjustment of teaching decisions significantly improves students' understanding level. Therefore, there is a significant difference in students' understanding level before and after teaching decision adjustment. The adjustment significantly improved students' understanding level, which proved that teaching decision adjustment oriented towards students' personalized learning needs was effective and helped improve their understanding level, thus further improving the teaching quality.

5 CONCLUSION

After in-depth research and analysis, this study discussed the classroom teaching decision optimization scenario oriented towards the personalized learning needs of students. The IPSO algorithm was introduced to optimize the multi-conditional factor classroom teaching decision optimization model. Teaching resources, contents and methods were adjusted at different teaching stages to meet students' personalized learning needs. The evaluation index results showed that the IPSO algorithm had better overall performance at the preparation, exploration and consolidation stages compared with the algorithm before optimization, indicating that the IPSO algorithm more effectively met the personalized learning needs of students, providing more accurate support for teachers to make appropriate teaching decisions at different teaching stages. The optimization comparison results showed that the IPSO algorithm found excellent solutions more efficiently and easily during the search process, further proving that the IPSO algorithm was effective in optimizing classroom teaching decisions. According to the comparison results of students' understanding level before and after teaching decision adjustment, it was found that the adjustment significantly improved students' understanding level, indicating that the teaching decision adjustment oriented towards students' personalized learning needs was effective, which helped improve their understanding level, thus further improving the teaching quality.

Combined with the research and analysis results of this study, the following conclusions were drawn. The classroom teaching decision optimization oriented towards students' personalized learning needs was an effective educational means to improve teaching quality and students' understanding level. The IPSO algorithm optimized teaching decisions, which provided more accurate support for teachers, and helped them develop decision-making plans of teaching resources, contents and methods adapting to different teaching stages.

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