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Research on Intelligent Learning Path Planning and Recommendation Algorithm in OMO Teaching Mode Based on Artificial Intelligence Grand Modeling

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ABSTRACT
OMO teaching mode based on artificial intelligence big model is one of the important future research directions and application landing forms in the future education field. The learning path recommendation algorithm based on big language model is constructed by integrating Transformer architecture, neural network architecture and self-attention mechanism. Combining it with the course knowledge graph, it links the learners with the knowledge system and visualizes the results of the intelligently planned learning path. The study shows that compared with several other algorithms, the personalized learning path recommendation algorithm based on AI big model has better convergence speed and stability. The optimal solution for learning path planning is found after only about 90 iterations. Taking “Chemical Process and Control Simulation” as the target course, the method in this paper gives the learning path and course. Through the questionnaire survey, the mean value of the four dimensions of pre-class pre-study, classroom exploration, post-class enhancement, and learning satisfaction is more than 3 points, which indicates that the OMO model and the teaching model of the artificial intelligence big model have a better experience.

Keywords: big model, artificial intelligence, knowledge graph, recommendation algorithms, learning paths

1. Introduction

In today's era of continuous development of science and technology, Artificial Intelligence (AI), as an emerging discipline, has been widely used in various fields, including the application of AI in education, which can not only provide students with personalized learning experience, but also provide intelligent support for the teaching process and curriculum arrangement [1-4].

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The OMO education model (Online+Mobile+Offline) is an education model that integrates online, mobile and offline forms based on AI, which makes comprehensive use of technologies and resources such as the network, mobile APPs, and real environment scenarios to provide users with diversified and personalized education services [5-8]. The OMO model has revolutionized the traditional education model , which overcomes some of the drawbacks existing in the traditional teaching mode and is more adaptable to the development needs of today's society, making learning more interesting, efficient, and effective [9-11]. The OMO model can customize learning recommendations for each student to meet his/her needs and level according to the individual differences in students' learning goals, interest preferences, and learning styles, etc.[12]. In the OMO model, AI, by analyzing students' learning data and behavioral patterns, it can generate learning resource recommendations to improve learning effectiveness and learner engagement [13-14]. In traditional education, students' learning paths are usually fixed and cannot meet the individualized needs of different students, while AI can intelligently design learning paths based on the structure of subject knowledge and students' learning journeys to provide students with the optimal learning sequence and progress [15-18]. In this way, students can follow the appropriate path according to their abilities and interests, and improve their learning results.

This paper focuses on the research of OMO (online-offline integration) education model empowered by the big model of artificial intelligence. In order to realize personalized learning path recommendation and planning in education, a learning path recommendation algorithm based on AI big model is proposed. Multidimensional interest labels and item value weights are utilized to obtain relevant interest data and generate user interest information sequences. Taking the user interest information sequence as the input value, the input information is processed through the neural network architecture of the big model, the Transformer architecture and the self-attention mechanism to complete the model to guide the model for interest understanding, prediction and learning path recommendation. The big model recommendation algorithm combines with knowledge graph to plan possible learning paths through learners' target learning objects and learning needs, and visualize the display. Finally, the practical application effect of the design method in this paper is verified through experimental tests.

2. OMO model and artificial intelligence big model teaching model construction

OMO, or Online-Merge-Offline, was first used in the e-commerce industry, also known as OMO business model [19].

Combined with the context of the times, it can be understood that the current OMO teaching model is a new type of teaching model that is student-centered, uses mobile technology and digital technology, allows the audience to master and understand knowledge through the information dissemination media, forms a scenario ecology in which the online and offline are integrated with each other, and realizes a new sample of personalized teaching and service-oriented teaching with dual social and economic attributes.

The OMO education model can realize accurate recording of teaching and learning data, and targeted checking of students' deficiencies, helping students to make decisions about information at any time. However, at the same time, it also shows that there are many limitations of pure online teaching, such as emotional communication barriers, a sense of communication is not strong, “screen-to-screen” monitoring is not in place, etc. Therefore, the emergence of these phenomena has prompted the integration of online and offline teaching to receive wider attention, and has become an urgent need and trend for the development of the field of education. The intelligent classroom interaction mode is shown in Figure 1.

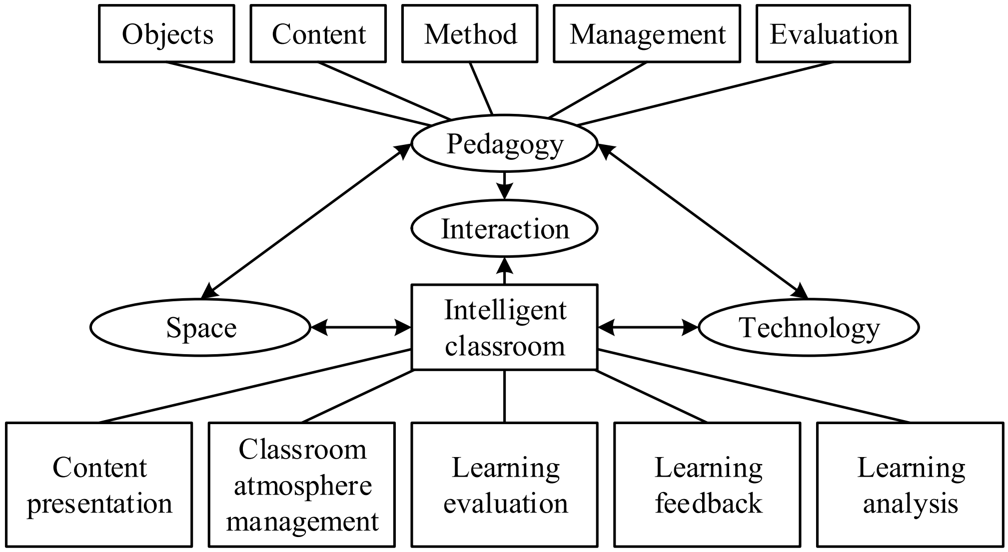


Fig. 1. Intelligent classroom interaction mode

Digital transformation empowers education and teaching, and is promoting the traditional teaching mode to the direction of intelligent and personalized development. AI+OMO normalized "smart classroom" construction practice research, exploring how to achieve online and offline integration of normalized teaching in ordinary classrooms, as well as how to optimize the design of teaching and learning through the empowerment of artificial intelligence.

With the rapid evolution of generative AI, multimodal big models are increasingly showing their advantages in multimodal content understanding and generation [20]. In the field of education, domestic and foreign scholars are still in the initial stage of research on intelligences. Early research focuses on the construction of intelligent bodies for knowledge sharing and optimization of its organization and management mode, and some research attempts to design educational intelligent bodies that can interact with learning to realize student-centered personalized online learning. In recent years, researchers have studied intelligences from the perspectives of the mechanism of cognitive learning and social cue design, emphasizing the higher-order meaning processing and interactive innovation of learning subjects. With the maturity of generative AI technologies such as big models, researchers have tried to construct a general-purpose intelligent body based on big language models, which can be used as a user interaction assistant to transform mathematical formulas. In addition, researchers try to utilize multiple general intelligences to simulate classroom interactions between teachers and students, and the experimental results show high similarity with real classroom environments in terms of teaching methodology, curriculum, and student performance.

3. Knowledge Graph Learning Path Planning Model Based on Large Model Recommendation Algorithm

3.1. Learning Path Recommendation Algorithm for Large Language Modeling

3.1.1. User Interest Modeling. Using multidimensional interest labels and item value weights to correspond to the capture of relevant interest data, in the process of data capture, different interest information feature parameter will be obtained, which can indirectly complete the corresponding analysis of user interest data to generate user interest model.

Utilizing the multidimensional interest label to obtain the processed direct expression interest information sequence $\overline{A}$ is:

$$\overline{A}=\frac{1-\tilde{\omega}_x}{x\sqrt{\ln\hat{B}\left(a_1+0.01\right)}}+\left\|B'+C'\right\|^{-2\tilde{\omega}_b} \tag{1}$$

where ω denotes the item value feature weight coefficient. x denotes the dominant user interest information feature value; $\hat{B}$ denotes the total amount of user data text. a_1 denotes the coverage of dominant user individuals with multidimensional interest labels; B' denotes the set of users involved in directly expressing interest information items. C' denotes the set of dominant interest labels; b denotes the dominant interest information in the collected user data.

Based on the principle of operation in Eq. (1), the sequence of users' potential interest information $\tilde{A}$ is calculated as:

$$\tilde{A}=\sum_{y=1}\frac{\left(1-\tilde{\omega}_y\right)\left(1+\tilde{\omega}_y\right)}{y\sqrt{\ln\hat{B}\left(a_2+0.03\right)}}+\left\|B''+C''\right\| \tag{2}$$

where y denotes the implicit (potential) user interest information eigenvalue. a_2 denotes the coverage of implicit user individuals with multidimensional interest labels. B'' denotes the set of users involved in the potential interest information items. C'' denotes the set of implicit interest labels.

Learning resource attribute information contains a combination of structured and unstructured data, which has a certain complexity, so in the process of calculating this type of information sequence, it is necessary to assign the collected indicators one by one, superimpose the user's interest value for different indicators, so as to generate the user's comprehensive interest value for computer learning resources, where the superposition of the normalization result is the same as the textual logic of the information sequence:

$$\eta\left(A\right)=\sum_{n=1}^{N}\hat{B}-\sqrt{\lambda_n^{\tilde{\omega}}\left(\lambda_n+\alpha_n\right)^{\kappa}}=\begin{cases}\lambda_1^{\tilde{\omega}}\in\left[0,0.6\alpha_1\right)\\ \lambda_2^{\tilde{\omega}}\in\left[0.6,1.2\alpha_2\right)\\ \lambda_3^{\tilde{\omega}}\in\left[1.2,1.8\alpha_3\right)\\ \lambda_4^{\tilde{\omega}}\in\left[1.8,2.4\alpha_4\right)\\ \lambda_5^{\tilde{\omega}}\in\left[2.4,3\alpha_5\right)\end{cases} \tag{3}$$

where $\eta\left(A\right)$ denotes the user's aggregate interest value in computer learning resources; λ_1, λ_2, λ_3, λ_4, λ_5 denote online computer courses, hands-on guides for intermediate programming projects, learning resources on programming language topics, learning resources with a short update cycle, and learning resources with a group focus, respectively; α_1, α_2, α_3, α_4, and α_5 denote the interest scales of the corresponding item classes; $n=[1,N]$ denotes the total number of sampled learning resource attributes; κ denotes the user interest feature structure factor.

Joint Eq. (1), Eq. (2) and Eq. (3) to construct a mathematical model of user interest containing interest labels with feature weights:

$$\delta=\frac{\sin\mu(\cos\mu-1)}{\tan\sigma^{-1}}+\overset{\leftrightarrow}{\vartheta}\left[f\left(\overline{A}+\tilde{A}\right)^{\tilde{\omega}}-\eta\left(A\right)\right] \tag{4}$$

Where δ denotes the mathematical model of user interest; μ denotes the time decay scale. σ denotes the user activity level. $\overset{\leftrightarrow}{\vartheta}$ denotes the learning resource feature vector. $f\left(\cdot\right)$ denotes the user demand function.

3.1.2. Transformer Architecture and Cued Learning Units. As a deep learning model, the Artificial Intelligence Grand Model incorporates the Transformer architecture, which processes input information, captures key information, and performs contextual learning through neural network architecture and self-attention mechanism [21]. In order to effectively capture the complex contextual relationships in the input sequence information, process the dependencies in the sequence data, and improve the accuracy of personalized recommendation, in this paper, we take the sequence of user's interest information (representing the user's needs) contained in δ as the input and optimally build the Transformer architecture by incorporating the multi-attention mechanism and the bi-directional long and short-term memory network (BiLSTM) in the big language model.

The application principle of the cue learning unit is shown in Fig. 2. The cue learning unit performs the user intent understanding task and the input text enhancement task through the mask language model, and generates GPT instructions to obtain the answers to the questions based on the input cue templates. After completing the actual input vector representation, the BiLSTM layer is utilized to extract the contextual relationships of the output vectors of the input layer and obtain the user's preference features for different resources. Then the output information of the BiLSTM layer is used as the input of the multi-head attention mechanism part to weight the preference feature information of the associated users and the attribute information of different learning resources, and the weighting results are output to the decoder part to decode the information. The information with weights is input to the BiLSTM layer in the decoder part for decoding process to further extract the input sequence features. The sequence feature data is then passed into the fully connected layer for stitching and fusion. In addition, the low-rank adaptation fine-tuning unit injects a trainable layer containing the rank decomposition matrix into each Transformer block to fine-tune the structure of the model to adapt it more effectively to the requirements of the user comprehension task. Finally, the spliced fusion results containing contextual features are generated as probability distributions via the Softmax function. Where each probability value corresponds to a potential learning resource, indicating the likelihood of each learning resource being recommended given the user preference information. Based on the probability distribution output from the SoftGmax layer, the design model will select the learning resource with the highest probability value as the personalized learning path recommendation result.

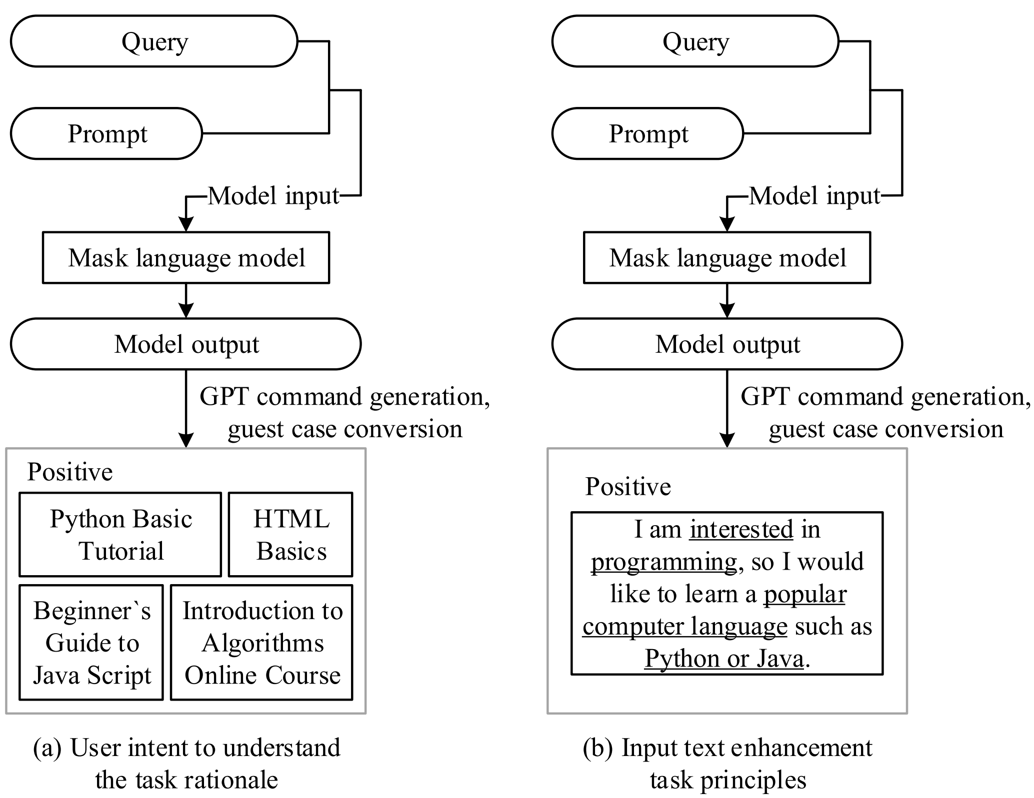


Fig. 2. suggests the principle of learning unit application

3.2. Construction of Knowledge Graph

This system aims to provide students with personalized and intelligent learning path planning services by using a large language model recommendation algorithm combined with a knowledge graph database (nodes.csv and relationships.csv files) extracted from the course to visually display the results of learning path planning.

Knowledge graph is a graphical structure for representing knowledge, which organizes and stores information in the form of entities, relationships and attributes. This graphical structure can help computer systems understand and reason about knowledge providing more intelligent information processing and retrieval [22].

Specifically, a knowledge graph contains the following elements:

Entities: represent things in the real world, such as students, courses, videos, knowledge concepts, etc. Each entity has a unique identifier in the knowledge graph.

Relationship: Describes the connection or association between entities and expresses the relationship between them. These relationships usually have specific semantic meanings, such as “subordinate”, “subject-object”, “sequential”, etc.

Attributes: contain additional information about entities or relationships to characterize them. For example, a student's attributes may include name, age, affiliation, etc.

The construction of knowledge graphs typically incorporates the extraction of knowledge from structured and unstructured data and the formation of graphical structured data representations by linking entities and relationships. In the scenario of learner learning knowledge path planning based on large-scale learning behavior knowledge graph, the form of dataset used in this paper exists in the form of knowledge graph structure, where the dataset is firstly represented based on ternary groups, and then the ternary groups are mapped to the nodes and relations of Neo4i using the graphical database Neo4i.

Where a circle is used to represent an entity, the information attached to the entity represents an attribute, and the arrow points to the relationship between two entities.

In the field of deep learning, the application of knowledge graph is given more flexibility, each node and relation in the knowledge graph can be embedded with vectors, and for the ternary, there exist additive representation and dot product representation of vectors, and the computation of the additive representation is shown in Equation (5):

$$V_{E1} + V_r = V_{E2} \tag{5}$$

Where V_{E1} is the vector embedding of entity one, V_{E2} is the vector embedding of entity two, and V_r is the vector embedding of the relationship between the two, and all the three vectors are (d,)-dimension vectors, with d being the vector embedding dimension, and the vectors embedded by the triple hold on vector addition.

The dot product representation of the corresponding embedded vectors of the triple is shown in equation (6):

$$V_{E1} \cdot V_{E2}^{T} = 1 \tag{6}$$

Similarly V_{E1} is the vector embedding of entity one, and V_{E2} is the vector embedding of entity two, both of which are (d,) dimension vectors. When the triad relationship holds, the result of the dot product of the two is 1. If there is a weight - a real number greater than zero - in the relationship, the result of the dot product of the two is numerically equivalent to the weight: if there is no relationship, the result of the dot product of the two is zero.

3.3. Planning of learning paths

Knowledge relationship is a prerequisite for learning content recommendation and an important basis for recommendation algorithm decision making. Learners can set their background knowledge and learning goals before learning. The recommendation algorithm maps the learner's background knowledge into the knowledge graph as the starting point for path planning. The model generates a set of alternative paths based on the user's current knowledge level, combined with the knowledge graph for initial screening, and then by evaluating the paths, the highest rated learning path is finally obtained, and all courses in the course are selected based on the learner's current knowledge level. In this process, path planning must fully consider the relationship between courses in the knowledge graph [23].

The relationships between courses in the knowledge graph are categorized into sequential and parallel relationships. The later courses generally contain part of the knowledge points of the earlier courses, and there are common and non-common knowledge points between courses, which can be connected through the common knowledge points in the knowledge map, and there are directed arrows connecting them in the knowledge map. Parallel relationship means that there are no common knowledge points between courses and courses, and there is no direct connection in the knowledge map. The recommendation process of path planning focuses on sorting these courses.

Learner's input query will be sent to the model for extracting target learning objects and learning needs. The raw input query needs to be converted into a collection by preprocessing. Then, the target learning objects are identified. Finally, learning requirements are obtained by corresponding from target learning objects and query keywords. The model will traverse the knowledge graph to find the set of learning paths containing all feasible learning paths and extract all possible learning paths of the set.

4. Intelligent Learning Path Planning and Recommendation Algorithm Analysis Study

4.1. Recommendation Algorithm Performance Testing

In this paper, six benchmark functions are selected to test and evaluate the performance of the recommendation algorithms: F1, F2, F3 are single-peak functions with only one optimal solution, which can be used to judge the convergence accuracy of the algorithms; F4, F5, F6 are multi-peak functions with multiple local optimal solutions, which can be used to judge the algorithm's ability to jump out of the local optimal solution. The comparison algorithms are BPSO algorithm, SBPSO algorithm, DSEBPSO algorithm. Among them, the DSEBPSO algorithm uses a dynamic strategy to improve the binary particle swarm algorithm.

The experimental results of the recommended algorithm for the large model and the three comparison algorithms on the six benchmark functions are shown in Table 1. The single-peak function has only one local optimal solution to test its convergence accuracy. From the table, it can be seen that in the single-peak functions F1, F2, and F3, the mean value of the recommendation algorithm of the large model is better than the other algorithms, indicating that this algorithm has a higher convergence accuracy than the BPSO, SBPSO, and DSEBPSO algorithms. The multi-peak function has multiple local optimal solutions to evaluate whether the algorithm is able to jump out of the local optimum. From the table, it can be seen that in the multi-peak functions F4, F5, and F6, the mean value of the personalized learning path recommendation algorithm of the large language model is significantly better than the other algorithms, indicating that it has a stronger ability to jump out of the local optimal solution. Overall, the variance of the recommendation algorithm of the large model is better than the rest of the algorithms in both single-peak and multi-peak functions, indicating that the stability of the algorithm has also been further improved.

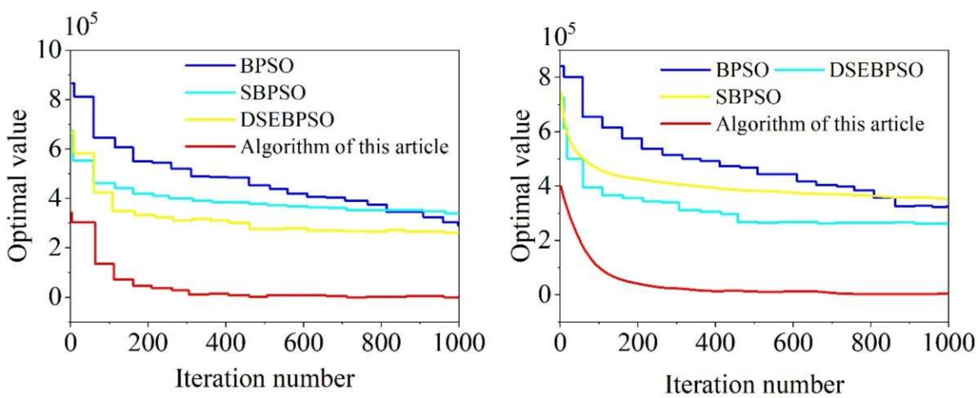
Table 1. Experimental results on six benchmark functions

Function	Index	BPSO	SBPSO	DSEBPSO	Algorithm of this article
Sphere	M	6.9845E+02	5.946E+02	1.925E+02	1.287E+02

	SD	3.142E+01	2.765E+01	2.356E+00	9.658E+02
Step	M	2.145E+03	1.935E+03	1.457E+03	9.882E+01
	SD	5.468E+00	5.472E+01	3.845E+01	2.642E+02
Rosenbrock	M	9.534E+02	9.052E+02	3.769E+02	2.541E+00
	SD	3.125E+02	3.528E+01	2.849E+03	2.633E+02
Rastrigin	M	9.014E+01	9.056E+02	9.022E+02	8.927E+01
	SD	3.325E+02	3.563E+00	1.526E+00	1.447E+00
Ackley	M	1.847E+00	1.695E-00	9.978E-02	3.625E-02
	SD	1.736E-02	1.784E-01	4.152E-02	3.022E-02
Grinwank	M	3.006E-02	2.635E-00	8.847E-03	5.471E-00
	SD	1.074E-01	7.421E-02	7.452E-03	5.634E-02

The convergence curves of the recommendation algorithm of the big model and the three comparison algorithms are shown in Fig. 3.

From the figure, it can be seen that the recommendation algorithm of the large model is better than the other algorithms in terms of convergence accuracy and jumping out of the local optimal solution. Due to the nonlinear adjustment of the viscous weights during iteration, the adaptation value of the single-peak function changes rapidly during the optimization process, and the success rate of optimization and convergence accuracy also increase significantly. For the multi-peak function problem with more local optimal solutions, the algorithm improves the particles with poor fitness values to increase the diversity of their populations, and at the same time promotes them to jump out of the local optimum thus enabling the algorithm to make better local exploration. The speed of convergence and stability of the learning path recommendation method implemented by the recommendation algorithm for large models also works better than other algorithms. Therefore, both with the increase in the number of knowledge points and the increase in the number of learners, it will make the learning path recommendation method have better convergence speed and stability, better meet the needs of learners, and present a better recommendation matching degree.



(a) Sphere (b)Step

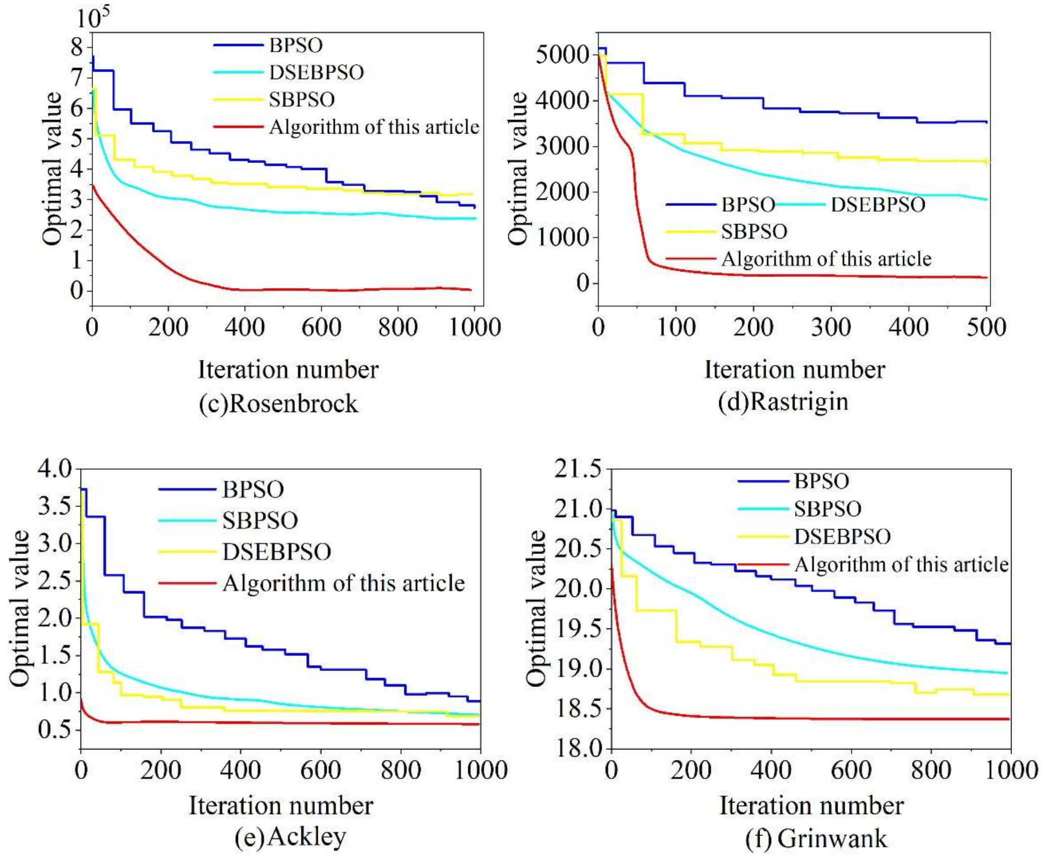


Fig. 3. The optimal value convergence diagram of the function

4.2. *Analysis of Intelligent Learning Pathway Planning Results*

In this paper, all the data of education courses are crawled from China University MOOC, which is a platform for collecting and organizing teaching resources. The platform undertakes the mission of the Ministry of Education's "National High-quality Courses" and provides more than 1,000 MOOC courses offered by famous Chinese universities to the public, many of which are offered by teachers from 985 universities, which breaks down the barriers between universities. After a preliminary analysis of the course pages of Chinese university MOOCs, the information we can get mainly includes the course name, the subject to which the course belongs, the instructor, the teaching institution, the course introduction, and the course syllabus. In addition to the "course details" page, each course also has a "course evaluation" page, where learners who have chosen the course can communicate with each other and rate the course. By clicking on the learner's avatar in the evaluation area, you can see the learner's personal information and history of course selection.

In order to verify the performance of the constructed learning path planning model proposed in the learning path planning problem, learners of the MOOC platform of Chinese universities are randomly selected, the courses in their history logs are added to the solution space, and the target courses are set for them artificially, and the optimal path is obtained through algorithmic solving. In order to make the algorithm better serve the research purpose of this paper-learning path planning, the commonly used parameters are set, and the results are shown in Fig. 4, which shows that the optimal solution of the problem is found by this model at about 90 iterations.

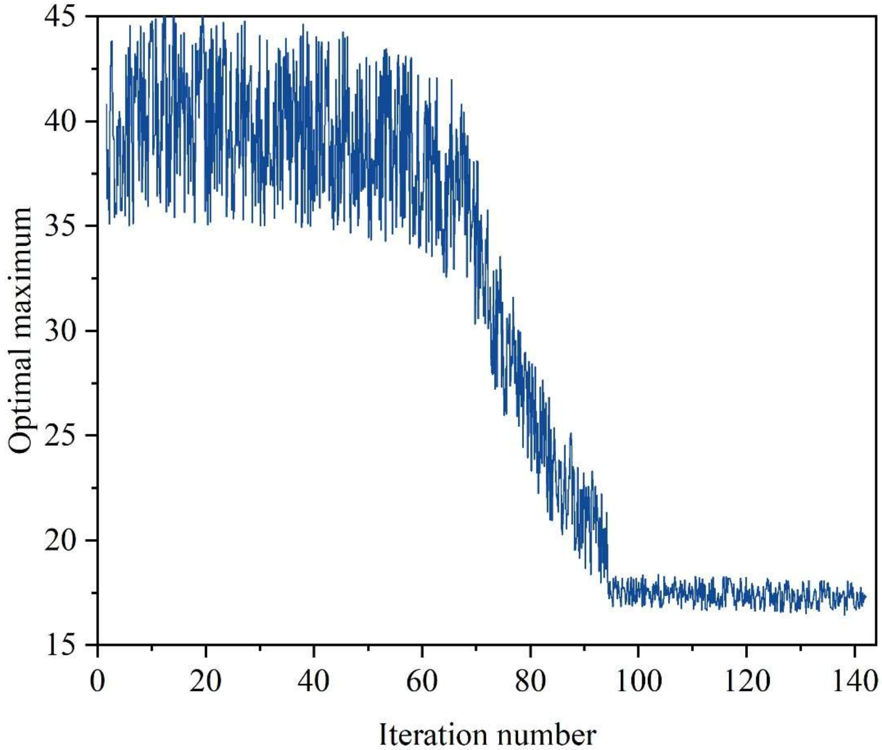


Fig. 4. Study path planning model performance analysis

Recommendation results as shown in Table 2, will be “chemical process and control simulation” as the target course, when the learner's user page shows that such as the student has studied “data structure”, the learning objectives of “deep learning”, many times running the algorithm gives the course recommendations include “machine learning” and “probability theory”, occasionally including “linear algebra” and “discrete mathematics” and other basic courses. But other irrelevant courses such as Principles of Databases and University Physics hardly appear in the recommendations.

Table 2. Results of Learning Path Planning

Knowledge background	Learning goal	Learning path planning
Data structure	Depth learning	Data structure → probability theory → linear algebra → discrete mathematics → machine learning
Machine learning Linear algebra Probability theory	Depth learning	Empty set (indicates that you can study the target course directly)
No	Civil procedure law	Civil code, civil law general and civil procedure law

According to the experiments to generate the learning path results are shown in Figure 5, for example, on the knowledge graph according to the learner's knowledge reserves and learning goals to plan the learning path in line with the current colleges and universities or the professional teachers of the recommended learning order, so this paper's method in the knowledge graph with the course before and after the order of the relationship between the learners to be able to plan for the learners to plan the appropriate learning path and course. However, because of the influence of the resources of the course, the interference term cannot be completely excluded. In order to provide learners with visualized prior-relationship mining results, prior-relationships are used as constraints to generate the final output of effective learning paths, and it can be seen that the higher the layer where the course is located, the more prior courses are needed, and the leaf nodes in the bottom layer are basic courses, which do not need to be prerequisite courses.

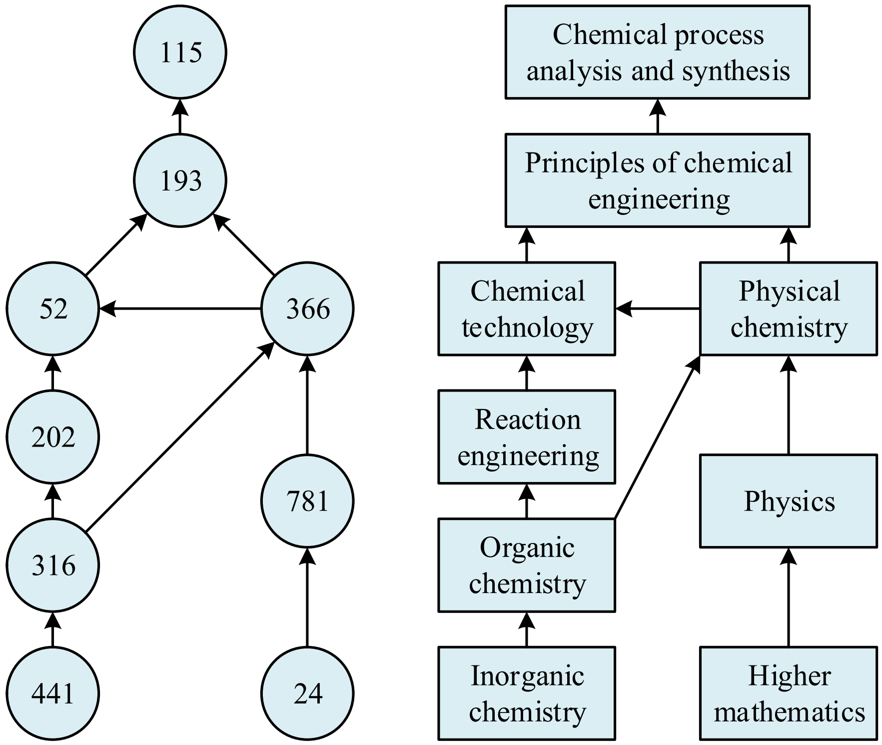


Fig. 5. Learning path

5. Learning analysis of the OMO teaching model of the Artificial Intelligence Big Model

This study takes all the learners in the experimental class of a university as the survey object, invites the learners to participate in the survey in a voluntary way, and the survey time is from June 1 to June 8, 2022, and finally recovers 86 pieces of sample data, of which 78 pieces of valid sample data, and the effective recovery rate is 90.7%. In order to further analyze the experimental class learners' learning as well as satisfaction with the OMO teaching mode based on the AI grand model, this study designed the Questionnaire for Learning of OMO Teaching Mode Based on the AI Grand Model by referring to the mature scales of the existing studies and combining with the specific experimental situation of this study. The questionnaire was scored on a five-point Likert scale: complete agreement was scored as 5 points, agreement was scored as 4 points, general was scored as 3 points, disagreement was scored as 2 points, and complete disagreement was scored as 1 point. The KMO value of the questionnaire is 0.85, which indicates that the validity of the questionnaire is good and can be further analyzed.

1) Mean value analysis of each dimension. The results of descriptive statistical analysis are shown in Fig. 6, the standard deviation of the pre-class preview stage is 0.78, the standard deviation of the classroom exploration stage is 0.70, the standard deviation of the post-class enhancement stage is 0.71, and the standard deviation of learning satisfaction is 0.73, and the standard deviation of all dimensions is less than 1, which indicates that the difference between the values of each group of data and their means is small. Among them, the mean value of the pre-class pre-study stage is 3.92, the mean value of the classroom exploration stage is 4.22, the mean value of the post-class enhancement stage is 4.20, and the mean value of the learning satisfaction is 4.23. It can be concluded that the mean value of the four dimensions is greater than the average value of 3, indicating that learners at all stages have a better learning experience, and are more satisfied with the OMO teaching mode based on the AI grand model. Among the four dimensions, the highest mean value in the classroom exploration stage

indicates that the learners have the best learning situation in the classroom exploration stage, and the lowest mean value in the pre-course preview stage indicates that the learners have a relatively poor learning situation in this stage, so the teacher should collect the learners' feedback on the pre-course preview stage in time, adjust the teaching strategy, and help the learners to better grasp the basic knowledge of the course content in the pre-course.

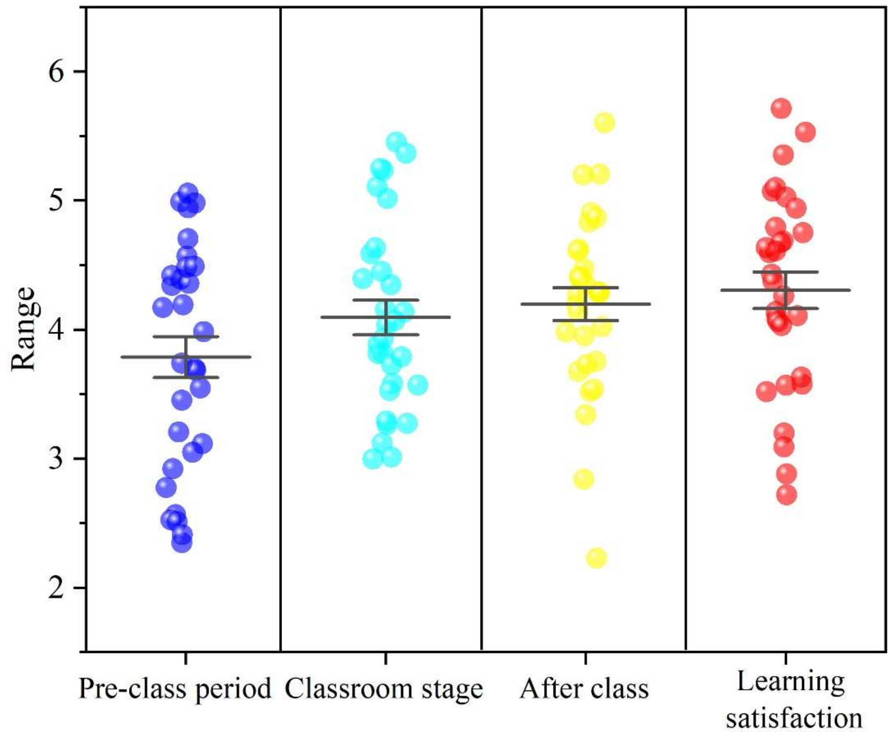


Fig. 6. The mean statistics of each dimension

2) Correlation analysis. SPSS 26.0 was used to test the normal distribution of the acquired questionnaire data, and the analysis results showed that the sample data conformed to normal distribution and could be further analyzed. In order to explore the correlation between the four variables of pre-class pre-study stage, classroom exploration stage, post-class enhancement stage and learning satisfaction, this study used SPSS 26.0 to conduct Pearson correlation analysis on the questionnaire data.

The results of the correlation analysis are shown in Figure 7, the six Pearson correlation coefficients between the pre-class pre-study stage and the classroom exploration stage, the post-class enhancement stage and the satisfaction with the OMO teaching model based on the AI grand model, the classroom exploration and post-class enhancement, the satisfaction with the OMO teaching model based on the AI grand model, and the post-class enhancement stage and the satisfaction with the OMO teaching model based on the AI grand model take the values ranging from 0.8-1, indicating a high degree of correlation between these four variables.

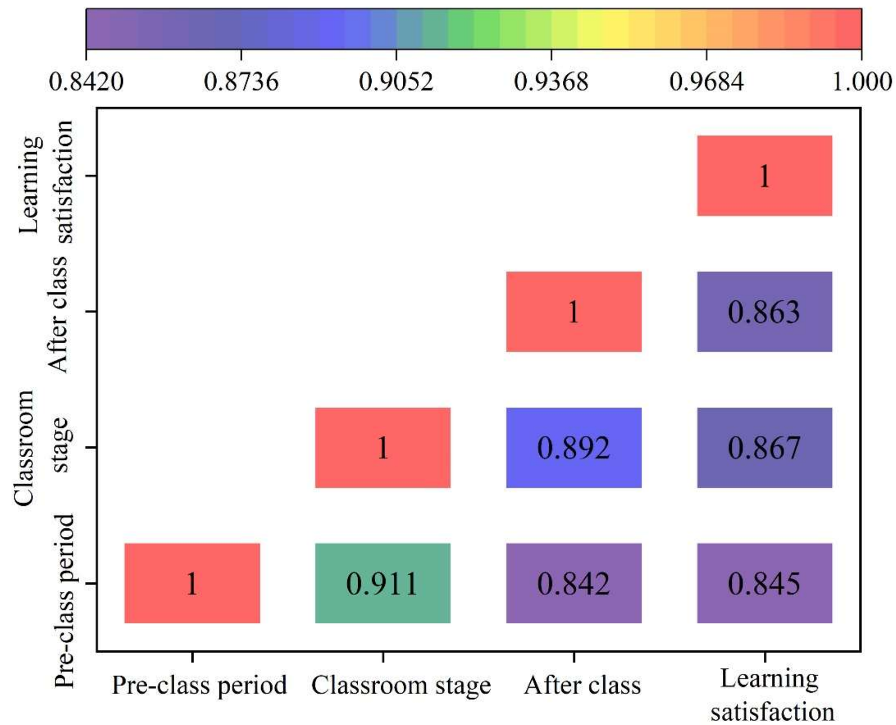


Fig. 7. Intervariable correlation analysis

3) Analysis of factors affecting learners' learning satisfaction. Linear regressivity analysis was conducted using SPSS 26.0 to analyze the influencing factors affecting the satisfaction about the OMO teaching model based on the OMO teaching model with artificial intelligence big model. Taking learning satisfaction as the dependent variable, the pre-class pre-study stage, the classroom exploration stage, and the post-class enhancement stage as the independent variables, R takes the value of 0.890, the value of R-squared is 0.812, and the value of adjusted R-squared is 0.794, which indicates that the pre-class pre-study stage, the classroom exploration stage, and the post-class enhancement stage can explain 80% of the variation in the learning satisfaction, and the model is well-fitted.

The regression model test is shown in Table 3, and the significance value of the F-test in the model is 0.001, which is all less than 0.05, indicating that the regression model as a whole is all significant, and that the pre-class pre-study stage, the classroom exploration stage, and the post-class enhancement stage all have a significant predictive effect on learning satisfaction.

Table 3. Learning satisfaction linear regression anova

	Sum of squares	Freedom	Mean square	F	Sig.
Regression	450.389	4	150.247	93.346	0.001
Residual error	120.451	78	1.624		
Total	570.84	81			

The results of the regression analysis are shown in Table 4, the significance values corresponding to the t-test of the pre-study stage, classroom exploration stage and post-course enhancement stage in the model are 0.035, 0.003 and 0.001 respectively, all of which are less than 0.05, which indicates that the pre-study stage, classroom exploration stage and post-course enhancement stage of the teacher have a significant predictive effect on the learning satisfaction, in which the standardized coefficient of the pre-study stage is 0.250, the standardized coefficient of the classroom exploration stage is 0.248, and the standardized coefficient of the after-school enhancement stage is 0.445. Accordingly, we get the standardized regression equations for predicting learning satisfaction by the pre-class pre-study stage, the classroom exploration stage, and the after-school enhancement stage:Learning satisfaction=0.250×pre-classroom pre-study stage+0.248×classroom exploration stage+0.445×post-class enhancement stage.

Table 4. study satisfaction linear regression coefficient table

Model	Unnormalized coefficient		Normalization factor	t	Sig.
	B	Standard error	Beta		
Constants	2.163	0.911		0.284	0.022
Pre-class preview	0.242	0.128	0.250	1.963	0.035
Classroom discussion	0.154	0.092	0.248	1.678	0.003
After class	0.546	0.157	0.445	3.849	0.001

6. Conclusion

In this paper, the OMO model is combined with artificial intelligence big model to establish a new education model. In order to realize personalized learning, a learning path recommendation algorithm based on the big model is proposed. Combined with knowledge graph, it is able to generate and recommend eligible learning paths. The main contributions of this paper are as follows:
1) Comparing the recommendation algorithm of the large language model with the other three algorithms, it outperforms the rest of the algorithms in terms of stability and convergence, and presents a better recommendation matching degree.
2) Learning the path planning method through the knowledge graph based on the large model recommendation algorithm, the optimal path is found by iterating up to 90 roles.
3) Applying the OMO and AI big model education model to actual teaching, it can be found that the learners' learning experience is better in the stages of pre-class pre-study, classroom exploration, and after-class enhancement.

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