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Article

Research and Practice on the Application of Artificial Intelligence in the Intelligent Teaching Management Platform of Housing Industry under the Perspective of Resource Sharing

Yuan You[1,*]

[1] Geely University of China, Chengdu, Sichuan, 641423, China
* Correspondence author: youyuan157352@163.com

Abstract: In recent years, artificial intelligence technology, especially deep learning, has been increasingly widely used in the field of education, and housing industry colleges and universities are facing the problems of dispersed teaching resources and low sharing efficiency. In order to improve the intelligent level of teaching management, the construction of an intelligent teaching management platform based on deep learning has become a key direction for the development of education informatization. This study constructs an intelligent teaching resource sharing platform for the housing industry based on deep learning algorithms, realizes personalized learning path recommendation through the LSTM model, and carries out test question recommendation experiments with A, B, and C students as objects. Methodologically, user behavior and basic information are collected, data cleaning and standardization are used to train the LSTM model, and compared and analyzed with traditional recommendation algorithms such as DT and IRT. The results show that in the test of class A students, the F1 value of this paper's method is 0.8502, and the MAE is only 0.0102; the F1 value of class B students is 0.8571; and the F1 value of class C students is 0.8233, which are all better than other algorithms. The conclusion points out that the platform can effectively improve the accuracy and reasonableness of teaching recommendation, especially for students with different learning styles showing good adaptability and generalization value.

Keywords: deep learning, LSTM model, personalized learning, teaching resource sharing, test question recommendation, intelligent teaching platform

1. Introduction

With the accelerated evolution of the world's great change that has not been seen in a century, strengthening science and technology popularization and education, and improving the scientific quality of the nation has become a fundamental project to sustainably enhance the country's innovation capability and international competitiveness. With the rapid development of science and technology, intelligent technology has been widely used in various fields, and in the field of construction, the application of intelligent technology also has great potential [1-2]. As an important part of buildings, construction equipment is crucial for architects and engineers [3]. Therefore, the introduction of intelligent technology in the teaching of construction industry courses will bring a richer learning experience to students [4].

Intelligent teaching management platform not only includes teaching equipment and office automation, but also has a perfect communication network system, which can provide a comfortable and convenient teaching environment by combining and utilizing multiple systems and technologies [5-7]. On the one hand, the intelligent teaching management platform can analyze students' learning data, identify their learning characteristics and weaknesses, and recommend suitable learning resources and practice topics based on this information [8-9]. On the other hand, the virtual labs and simulators provided by the platform can provide students with more practice opportunities and space for independent exploration, and promote the cultivation of their practical operation and problem solving abilities [10-12]. It can be seen that the application of intelligent teaching management platforms in the construction field has made significant progress, providing more opportunities and resources for teaching and learning [13-14]. Based on this, teaching management platforms for the housing industry are studied with a view to enhancing students' understanding of specialized knowledge and their degree of mastery of professional skills, as well as enhancing their adaptability to corporate positions in the housing industry [15].

Under the background of digital education transformation in the new era, how to realize the efficient allocation and personalized recommendation of educational resources in colleges and universities has become the core topic of teaching informatization construction. Especially in housing industry-related institutions, the courses are highly practical, the resources are diverse, and the differences in students' abilities are significant, and these characteristics pose challenges to traditional teaching management. Along with the maturity of artificial intelligence technology, deep learning, especially recurrent neural network (RNN) and long short-term memory network (LSTM), has gradually demonstrated powerful data mining and learning prediction capabilities. By capturing the time-series characteristics of learning behaviors, AI models can provide students with dynamically adjusted learning paths and personalized teaching resources. The openness and interactivity of the network platform further amplifies the advantages of the intelligent education system and makes personalized teaching from theory to reality. Although many colleges and universities are currently carrying out online teaching, they lack the support of intelligent recommendation systems, the teaching content is poorly matched to students' learning styles, and learning motivation is difficult to sustain. Constructing a teaching platform that integrates deep learning not only helps to improve the utilization rate of resources, but also provides real-time feedback data for the evaluation of education quality and assists in the scientific decision-making of teaching.

In this paper, a personalized learning model with LSTM as the core is constructed, which combines the user's basic information, learning behavior and resource characteristics to realize the learning path recommendation. The experimental session takes three types of student groups as the object, designs the comparison test task, and introduces the teacher's manual recommendation as the evaluation standard to assess the algorithm performance from the dimensions of F1 value, MAE and standard deviation of correct rate. Finally, the practicality of the model and student satisfaction are verified through the teaching practice on the platform, and a “cooperative-inquiry” learning model is constructed to improve the quality of teaching interaction.

2. Construction of a shared platform for teaching resources based on deep learning

2.1. Personalized learning based on deep learning algorithms

Deep learning (DL) specifically refers to machine learning based on deep neural network models and methods, which uses deep neural networks to automatically learn complex representations and features from data by simulating the connections between neurons in the human brain in order to solve a variety of practical problems. In the process of constructing personalized learning models using deep learning techniques, several steps are involved: first, data preprocessing, a process that includes operations such as data collection, data cleaning, and data normalization [16]. Next, a suitable model is designed according to specific needs, and then the model is trained with a large amount of data to optimize its performance. This is followed by model evaluation and model tuning. Finally, the optimized model is applied in real scenarios for personalized learning material recommendation and learning path planning.

2.1.1. Data pre-processing

This study mainly relies on three types of data: user behavior data, basic user information, and teaching resource information Users may adjust their clicking, browsing, and other behaviors due to factors such as network speed, stability, or attractiveness of the content, which leads to poor data quality or samples unrelated to the target when collecting user behavior data, which in turn can negatively affect the training process of the deep learning model. The purpose of data preprocessing is to improve the generalization ability of the model and ensure that the model can learn features that meet the design requirements during the training process, and this study mainly adopts data cleaning, data denoising, and data standardization to perform preprocessing operations on the collected sample data.

2.1.2. Recurrent Neural Networks

Unlike traditional feed-forward neural networks, recurrent neural networks (RNNs) have a feedback mechanism that captures temporal dependencies in sequential data by using the output of the previous moment as the input of the current moment. At each time step, the RNN receives an input vector and a hidden state vector, combines them via a nonlinear function, and then produces an output vector and a new hidden state vector.

where the matrices U,W,V are the weights of the input layer, the hidden layer and the output, respectively. x is the input, o is the output and t is the moment. Assuming that the input layer has i neurons and the hidden layer has h neurons, the hidden layer output is shown in equation (1).

$$h_t = \sigma(z_t) = \sigma(U_{h\times i}x_t + W_{h\times h}h_{t-1} + b) = \sigma(\begin{bmatrix} U_{h\times i} & W_{h\times h} \end{bmatrix}\begin{bmatrix} x_t \\ h_{t-1} \end{bmatrix} + b) \tag{1}$$

σ is the activation function and b is the offset of the linear relationship. The relationship between the output layer and the hidden layer is shown in equation (2) and the relationship between the predicted value and the output value is shown in equation (3).

$$o_t = Vh_t + c \tag{2}$$

$$\hat{y}_t = softmax(o_t) \tag{3}$$

The predictive power of the model is measured using the model's coefficient of determination R^2. Where $\overline{y_i}$ denotes the average value of y_i, and R^2 ranges from 0 to 1, indicating the degree of correlation between the predicted value and the true value of the target variable, and the larger the value, the better the prediction.

$$R^2 = \frac{\sum_{i=1}^{n}(\hat{y}_i - \overline{y_i})^2}{\sum_{i=1}^{n}(y_i - \overline{y_i})^2} \tag{4}$$

2.1.3. LSTM model

LSTM is a special kind of RNN, which can alleviate the gradient vanishing and long-term dependence problems to some extent by introducing a gating mechanism to control the flow of information and the forgetting process, and the structure of LSTM unit is shown in Fig. 1.

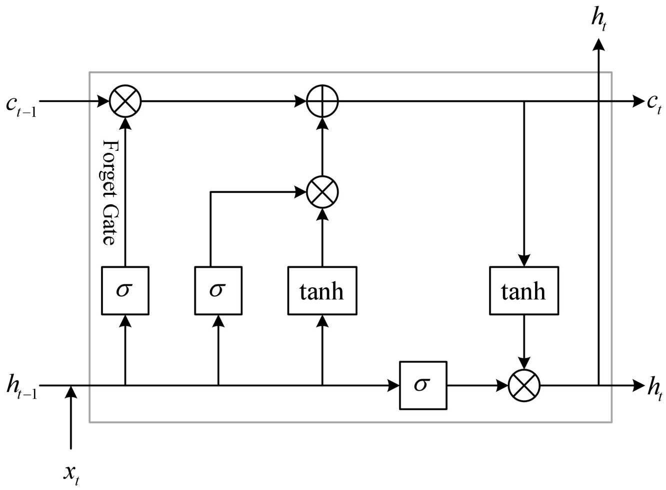

Figure 1. Structure of LSTM unit

In the figure, tanh is the hyperbolic tangent activation function and σ is the sigmod function. Each LSTM cell has three gates, the forgetting gate, the input gate and the output gate [17].

The forgetting gate decides when to discard information from the memory cell. It is controlled by a sigmoid function that outputs a value between 0 and 1, indicating the proportion of information to be forgotten, and the computational expression is shown in equation (5).

$$f_t = sigmoid(W_f \cdot [h_{t-1}, x_t] + b_f) \tag{5}$$

The input gate decides which new information will be stored in the memory cell, the sigmoid activation function is used to decide the part of the update, and the tanh activation function generates the candidate values, and the computational expression is shown in Equation (6).

$$c_t = f_t \times c_{t-1} + sigmoid(W_i \cdot [h_{t-1}, x_t] + b_i) \times \tanh(W_c \cdot [h_{t-1}, x_t] + b_c) \tag{6}$$

The output gate determines the output at the next time. First, the output gate uses the sigmoid activation function to decide which parts of the memory cell will be output, then this value is multiplied with the value of the tanh activation of the memory cell to get the final output, the computational expression is shown in equation (7).

$$h_t = sigmoid(W_o \cdot [h_{t-1}, x_t] + b_o) \times \tanh(C_t) \tag{7}$$

2.1.4. Personalized Learning Modeling

The user basic information data, learning behavior data and teaching material information data after data cleaning and normalization are divided into training set and test set, the LSTM model is established by using the training set data, the model is verified by using the test set, and finally the personalized learning model is built, and the modeling process of "personalized learning" is shown in Figure 2.

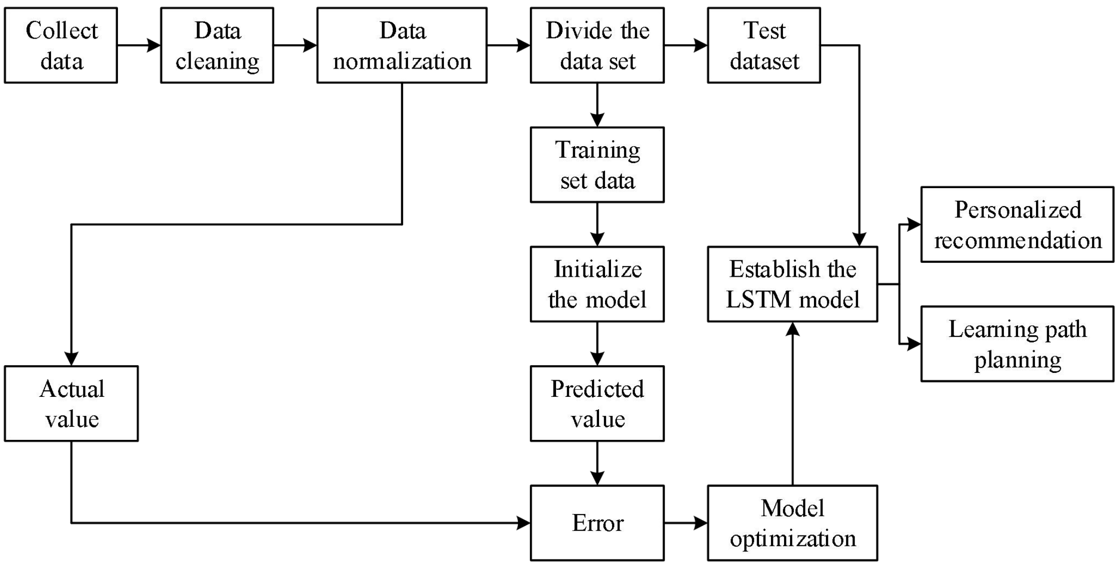

Figure 2. The modeling process of "Personalized Learning"

By analyzing the user's basic information, learning behavior data, describing the user's learning style and interest preferences, combined with the characteristics of learning resources, to complete the recommendation of learning materials. Analyze the user's learning objectives and existing knowledge level, and use the deep learning model to adjust the learning path planning in real time.

During the training process, the F1 score evaluation index was used to assess the performance of the model, and the accuracy and generalization ability of the model was gradually improved by continuously adjusting the model structure, optimizing the algorithm and parameter settings.

2.2. Design and realization of the resource sharing platform

The platform uses HTML, CSS, JavaScript, Vue3.js, uni-app and other technologies to develop the user interface, Java language to implement the business logic processing, integrates the deep learning model, and MySQL database to store the user behavior data, basic user information and learning resources.

The overall architecture design involves planning and defining the overall structure of the system, the components, the relationship between them, and how they interact. The overall architecture of this teaching resource sharing platform is divided into four layers, including data layer, processing layer, application layer and user interaction layer, and the overall architecture is shown in Figure 3.

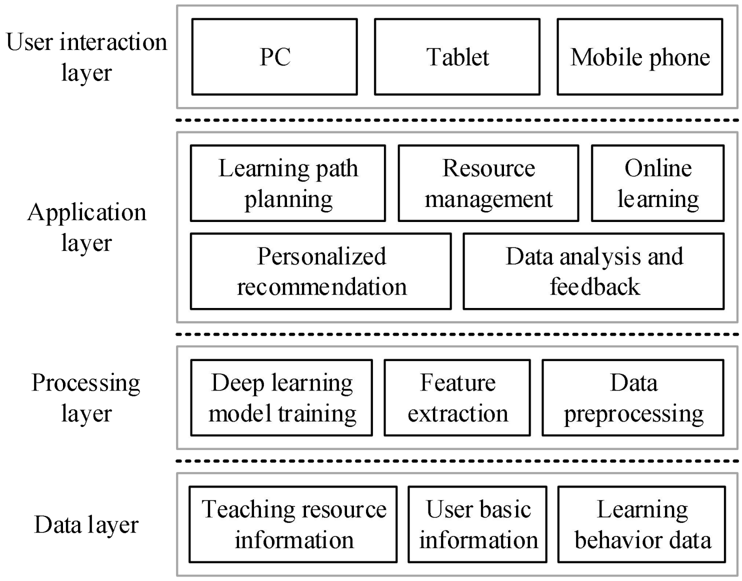

Figure 3. Overall architecture diagram

3. Experimentation and analysis

3.1. Experimental design and data set description

In this section, five methods are selected for comparison experiments, including Random, a random recommendation selection strategy, DT, a selection strategy based on multiple decision trees, IRT, a selection strategy based on Item Response Theory, and Methods. Experimental environment: experimental platform Windows11, program implementation using python3.7.

Experimental design: a group of target students in each of the three categories of A, B and C were selected for test question recommendation and evaluation observation. The experimental test was conducted at the time point after the students' historical answer records reached 30 questions. Taking category A students as an example, the algorithm in this paper recommended 10 test questions for 10 category A students respectively, totaling 100 questions, and 20 recommended test questions were obtained by removing the duplicate test questions among them. At the same time, in the case of mutual non-communication, two experienced teachers were asked to recommend two groups of 10 questions, respectively, to get 19 effective test questions, with the teacher's recommendation results to evaluate the accuracy of the algorithm recommendation. Similarly, three groups of students, A, B, and C, were tested for recommendation and response respectively, and test data were obtained. The same method is used to obtain the recommendation test results of the remaining three comparative recommendation methods (Random, DT, and IRT), and the test result data obtained from the three types of students and the five recommendation methods are analyzed to compare the performance in terms of the common indicators of the model, the recommendation accuracy, and the reasonableness of the recommendation, respectively.

3.2. Evaluation indicators

In order to evaluate the effectiveness and accuracy of the algorithm, a variety of metrics were used to comprehensively assess the performance of the algorithm.

(1) Precision, Recall and Fl

Precision rate, recall and Fl metrics are used to evaluate the performance of this paper's method and other comparative methods in terms of recommendation algorithm models. Precision rate, recall rate and F1 are specifically defined as follows:

$$precision = \frac{TP}{TP+FP} \tag{8}$$

$$recall = \frac{TP}{TP+FN} \tag{9}$$

$$F1 = \frac{2*precision*recall}{precision+recall} \tag{10}$$

where TP in Eq. denotes the number of recommended test questions that correctly hit the teacher's recommended test questions. FP indicates the number of recommended test questions that fail to correctly hit the teacher's recommended test questions. FN that the algorithm recommended test questions in the number of teacher-recommended test questions are not included.

(2) MAE

MAE (Mean Absolute Error) measures the mean of the absolute error between the predicted value and the actual value, which is used here to reflect the difference in the positive response rate between the results of the test question recommendation and the statistical expectation, i.e:

$$MAE = \frac{\sum_{i=1}^{n} | predicated_i - actual_i |}{n} \tag{11}$$

where n is the number of test questions, $predicated_i$ is the predicted positive response rate value of the test questions for that student, and $actual_i$ is the true expected positive response rate value for that class of students.

(3) Standard deviation of the ideal positive response rate

The test question recommendation problem is similar to the “optimal” tendency of common product recommendation, in that the positive response rate of the students in doing the test questions is not as high as possible. According to the concept of “three-zone theory” proposed by Noel Tichy in the cognitive field, the positive response rate for different types of students to achieve optimal learning results varies within a certain range.

The range of optimal positive response rates varies among the three types of students. The expected positive response rate of test questions recommended to different students depends on a number of factors such as the difficulty of the test questions and the knowledge level of the students. Based on the analysis of the historical data of the students in the category and the answer records of the students, the historical estimated correct response rate is found, and close to this range, it is considered to have found a suitable range for the students, in which the students will learn better.

As a result, the correct response rate used in this paper, defined as CRR (Correct response rate), i.e:

$$\overline{CRR} = \frac{Right}{Total} \tag{12}$$

Where Total is the total number of responses of the group of students of the type to which the student belongs in the recommended test questions, Right is the number of correct responses of the students of the type in the recommended test questions, $\overline{CRR}$ can reflect the actual difficulty of the recommended questions for this type of students.

3.3. Analysis of results

Completion of the experiment, the comparison of indicator data of the test results of the students of category A and C is shown in Tables 1 to 3. According to the experimental results, comprehensive observation of various types of data comparison table. From the table, it can be seen that comparing the decision tree algorithm, the algorithm designed in this paper has a good performance in precision rate, recall rate and F1 index, at the same time, after optimizing the sub-module and improving the performance of the prediction network, the overall ability of the model has a small increase, which can reflect that this paper's method has a higher performance than other models. In terms of the MAE index, this paper's method has the best performance, and the mean error values are all lower. For example, in the test results of class A students, the MAE value of this paper's method is only 0.0102. In terms of CRR standard deviation, this paper's method has the best recommendation with the smallest CRR standard deviation, which indicates that it is the closest to the ideal correct response rate, in a more expected range, and therefore more reasonable. Among the three categories of A, B and C students, the standard deviation of C students with poorer foundation is the largest, reflecting that the algorithm needs to be improved to give more consideration to the reasonableness of the recommendation for C students. In addition, from the point of view of the number of knowledge units (KUs) included in the recommended test questions, the method in this paper has good diversity in the recommended test questions while perfecting personalization.

Table 1. Comparison of index data of test results of class A students

	Precision	**Recall**	**F1**	**MAE**	**Standard deviation**	**KU**
Random	0.519	0.7369	0.6088	0.0452	0.0204	1,2,4
DT	0.5831	0.7366	0.6514	0.0282	0.002	2,3,4
IRT	0.6112	0.5787	0.5943	0.0558	0.0308	1,2,4,5
MDT&CD -LSTM	0.7998	0.8419	0.8206	0.0204	0.0023	1,2,4
Ours	0.8095	0.8944	0.8502	0.0102	0.0011	1,2,4

Table 2. Comparison of index data of test results of class B students

	Precision	**Recall**	**F1**	**MAE**	**Standard deviation**	**KU**
Random	0.6367	0.7367	0.6832	0.0224	0.0176	1,2,4,3
DT	0.6663	0.7372	0.6997	0.0211	0.0103	1,2,4
IRT	0.737	0.8236	0.7779	0.0171	0.0126	1,2,4
MDT&CD -LSTM	0.7893	0.8827	0.8337	0.0105	0.0022	1,2,4
Ours	0.8331	0.8823	0.8571	0.0119	0.0018	1,2,4

Table 3. Comparison of index data of test results of class C students

	Precision	**Recall**	**F1**	**MAE**	**Standard deviation**	**KU**
Random	0.571	0.7499	0.6487	0.026	0.0046	1,2,4,5
DT	0.6839	0.8125	0.7428	0.0228	0.0119	2,3,4
IRT	0.6498	0.8119	0.722	0.0199	0.014	1,2,4,3
MDT&CD -LSTM	0.7368	0.8755	0.8001	0.0171	0.004	1,2,4
Ours	0.7778	0.8748	0.8233	0.0138	0.0034	1,2,4

4. Platform-based “cooperative-inquiry” teaching model construction

4.1. Practice design and steps

4.1.1. Practice design

This study carries out a practical session of “cooperative-inquiry” learning on the platform, and takes students of a school as the research object, carries out a semester's preliminary study of cooperative-inquiry learning experiment based on the platform, and in the course, conducts a questionnaire survey on the learning effect of 50 students in the class, and analyzes and summarizes the results of the study.

4.1.2. Practical steps

Building the practical environment, including the establishment of platforms and the organization of reference and experimental classes. Establishing the teaching curriculum and the number of experimental and reference classes. The specific implementation process of the platform-based “cooperative-inquiry” model is as follows:

(1) Two weeks were spent on introducing and training students to familiarize themselves with the platform and establishing group assignments.

(2) Twelve weeks of teaching and learning based on the content modules.

(3) Teachers guide, combined with the advantages of the platform, to collect rich information, to lead to the topic of learning, and to establish teaching objectives.

(4) Combined with the teaching objectives, independent exploration, combined with the platform to

expand their knowledge background, collect relevant information for learning, and then the groups to explore and exchange.

(5) Each week the group reports, the next week for group discussion, the teacher comments and plans the next week's learning content. For example, in the fourth teaching week, students study in groups according to the teacher's planning of teaching content, and in the fifth teaching week, a lottery is held to determine which group will report on the content of the teaching, with the group leader assigning the report, and other groups asking questions or proposing topics for discussion after the report.

(6) Summarize according to the discussion questions. For example, students will discuss the questions and after the 5th week of class, students will reflect and explore the course content on the teaching platform.

(7) Teachers can propose appropriate tasks to consolidate the practice of learning content based on the lesson summary. For example, in the 6th week, each group conducts a stage-by-stage summary, and the teacher, in conjunction with the return of each group, conducts a content critique, summarizes and determines the content of the next week's teaching.

(8) Use 2 weeks to conduct questionnaires, examinations, and compare the results of the examination with the results of the questionnaire to see if they are consistent with a positive distribution. To see if the students can feel that different teaching methods are used through the questionnaire, the examination will mainly see if these different teaching methods can reflect different grades, and then to see if these grades are related to the choice of teaching methods.

4.2. Analysis of the learning environment

4.2.1. “Cooperative-inquiry” learning environments

The “cooperative-inquiry” learning environment refers to the learning activities that promote learners' active participation in cooperation and inquiry, which includes the organizational environment, spatial environment, hardware environment and resource environment for cooperative learning, etc. The “cooperative-inquiry” learning environment is shown in Figure 4. The creation of the learning environment needs to follow the guidance of learning theory, the design of the learning environment is also the practice of specific theories of learning, Jonathan's constructivist elements of the learning environment is the basis for the design of collaborative learning environment [18]. Therefore, it is important not only to create new learning environments, but also to make full use of existing learning environments.

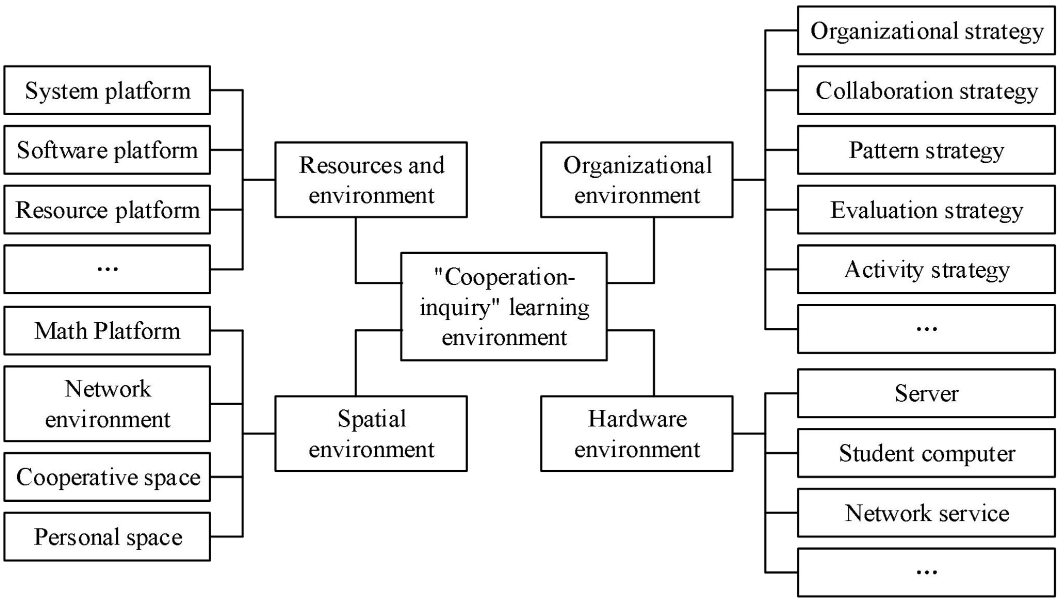

Figure 4. "Cooperation-Inquiry" Learning Environment

4.2.2. Platform-based learning environment

The combination of cooperative learning and network teaching platform is a reintegration of the learning environment, and it also changes the way of students' learning communication. Cooperative learning under the network platform can greatly mobilize the learning motivation of the learners, enhance the cooperative communication and innovation between the learners, strengthen the sense of mutual assistance and improve the learning efficiency.

Constructing the learning environment on the network platform also needs to be considered from these four aspects. First, the organizational environment of learning needs to be restructured on the platform, which should be carried out based on the functions provided by the platform. If the platform already has the function of student grouping, different forms of grouping can be used according to the specific teaching situation, so that the organizational environment is diversified, and then better with the development of cooperative learning. In terms of hardware environment, if the platform itself is an online network platform, the interactivity of the network provides the basis for cooperative learning environment. In addition, many activity modules on the platform can also provide sufficient support for the development of cooperative learning. In terms of the resource environment, the online teaching platform has a great advantage, and many modules on the platform can display and present a variety of rich learning resources for learning activities. In view of the functions of the modules on the platform, it is proposed that the core elements for building a cooperative learning-based environment should include four aspects, such as shared information resources, interactive tools, cooperative space and personal space.

5. Practical studies

5.1. Analysis of satisfaction

The 50 students in the class were surveyed through the cell phone questionnaire applet, the questionnaire content was "'modern educational technology' based on the platform teaching satisfaction", the questionnaire was sent to 50 students, 50 valid questionnaires were retrieved, and the degree of satisfaction is shown in Table 4. Table 4. It can be seen that the 50 students in the class only individual dissatisfaction with the online and offline hybrid teaching of this course, the overall by the students satisfied and like.

Table 4. Satisfaction situation

Options	Very Satisfaction	Satisfaction	General	Discontent	Disrelish
Number	20	26	3	1	0
Proportion (%)	40	52	6	2	0

5.2. Analysis of offline and online learning effects

5.2.1. Online Learning

The average score rate of the learning situation is shown in Table 5. From the table, it can be seen that the class has completed all the tasks of watching the online learning videos, the online interactions were completed well, the chapter tests and discussions were above 88 points, some individual students scored low on the chapter tests, and a few students did not complete the discussions well. Overall, students completed the online portion of the course in good overall condition.

Table 5. Average score

Learning project	Online video task	Interacts	Chapter test	Discuss
The average fraction is (%)	100	92.3	88.9	88.6

5.2.2. Offline classroom performance

Combining offline class attendance, participation and class performance, the classroom score rate is shown in Figure 5. It can be seen that the overall attendance of students is high, they usually actively participate in all classroom interactions, and their classroom discipline and performance are good. The overall classroom attendance is good.

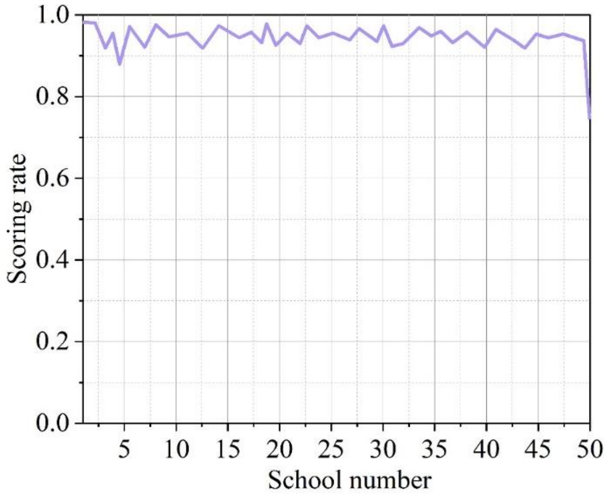

Figure 5. Classroom score

5.2.3. Analysis of Students' Laboratory Work and Final Examinations

(1) Experimental work situation

The score rate situation of experimental works is shown in Figure 6, which shows that the students' experiments are completed well, and only individual students have a lower average score due to the fact that they have submitted three assignments less. In addition, in the experimental works, some of the experiments require students to design and synthesize independently, and through learning and practicing, students can not only apply the knowledge points well in the experimental works, but also design independently on the basis of the correct application of the knowledge points, and most of the students' works are very creative and effective. It can be seen that learning through the platform not only mobilizes students' interest and enthusiasm in learning, but also enhances students' creative ability and innovative thinking to a certain extent.

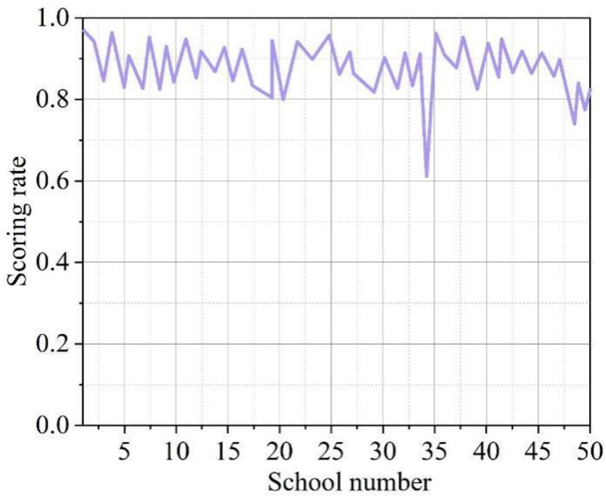

Figure 6. Experimental work rate

(2) Final examination situation

The specific performance of the final examination is analyzed as shown in Table 6. From the table, it is known that the overall results of the final examination of the class are good, the average score is higher than 88, and the excellence rate is 50%. The overall teaching effect is good.

Table 6. Analysis of the final examination

grade	90~ 100 (excellent)	80~ 89 (good)	70~ 79 (medium)	60~ 69 (pass)	<60 (inferior)
Number of people	25	20	3	2	0

Proportion (%)	50	40	6	4	0
Mean value			88.65		

6. Conclusion

The results of the platform's practice show that students' overall recognition of the deep learning-based teaching platform is high. In the satisfaction survey, 80% of the students indicated that they were “very satisfied” or “satisfied”, and only 2% indicated that they were “dissatisfied”. For online learning, the completion rate of video tasks was 100%, the average score rate of chapter tests was 88.9%, and the interaction score was 92.3%. The offline classroom has a high attendance rate, positive interaction, and an overall good average score rate for experimental works, reflecting the obvious effect of the platform in enhancing students' hands-on ability and innovative thinking. The final assessment results further verified the teaching effect, with the average class score reaching 88.65 and the excellence rate of 50%. Compared with traditional teaching, the platform not only optimizes the choice of learning paths, but also enhances students' motivation to learn independently and improves the overall teaching effectiveness. In conclusion, this intelligent teaching management platform shows significant advantages in resource integration, personalized recommendation and practical ability cultivation, and has good application prospects.

About the Author

Yuan You (1986-), male, Han Nationality, born in Luzhou, Sichuan province, bachelor degree, assistant researcher/engineer. His main research interests include computer network and artificial intelligence.

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