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iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 13 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i13.41913

PAPER

Learning Path Recommendation of Intelligent Education Based on Cognitive Diagnosis

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ABSTRACT

Many learning path recommendation methods of intelligent education have been proposed and implemented. However, many of them have problems or limitations, which may result in unsatisfactory recommendation results. Therefore, this research aimed to study the learning path recommendation method of intelligent education based on cognitive diagnosis. Combined with a cognitive diagnostic model (CDM), personalized and accurate learning paths were recommended to students. This study fully considered the multidimensional features of interaction between students and knowledge when designing the CDM, described the cognitive process, and provided a comprehensive ability modeling method based on cognitive rules. A neural matrix decomposition model was constructed, which incorporated the personality features of students' comprehensive ability level based on cognitive rules, thus obtaining their predicted scores in various knowledge and skills learned. The model consisted of three parts, namely, the generalized matrix decomposition part, the multi-layer perceptron part and the NeuMF layer. Finally, the experimental results verified that the constructed model was effective.

KEYWORDS

cognitive diagnosis, intelligent education, learning path recommendation

1 INTRODUCTION

With social development and the improvement of education level, the demand for personalized education has been increasing day by day [1–6]. The traditional "one-size-fits-all" teaching method can no longer meet the needs of modern education, because the learning ability, interests and progress of each student are different [7–10]. The development of artificial intelligence (AI) and big data technology has made intelligent education possible. The learning needs of students can be better understood by collecting and analyzing their learning data, thus teaching them more accurately and effectively [11–12]. A CDM is a tool measuring the cognitive

Lou, P. (2023). Learning Path Recommendation of Intelligent Education Based on Cognitive Diagnosis. *International Journal of Emerging Technologies in Learning (iJET)*, 18(13), pp. 104–119. https://doi.org/10.3991/ijet.v18i13.41913

Article submitted 2023-04-01. Resubmitted 2023-05-26. Final acceptance 2023-06-02. Final version published as submitted by the authors.

ability of students, which helps understand their mastery of knowledge and skills, and then more suitable learning resources can be provided for them based on this information [13–17]. The learning path recommendation method of intelligent education based on cognitive diagnosis involves the use of modern AI technology, which recommends personalized and accurate learning paths to students by combining with the CDM [18–19]. Through personalized learning path recommendation, students can choose the most suitable learning resources based on their cognitive level, interests, and learning progress, thus improving their learning efficiency and effect.

Current learning platforms generally have problems, such as knowledge fragmentation, information redundancy, and confusion of learning paths, which cannot meet the autonomous learning needs of learners. Liu et al. [20] structurally represented subject knowledge using the features of knowledge graph, and designed a learning path recommendation system based on the graph. This system expanded the knowledge graph system using node centrality and weights, which better expressed the structural relationships between knowledge. The particle swarm fusion algorithm adopting multiple rounds of iterative simulated annealing was used to recommend learning paths. Valuable learning path patterns were discovered from the online learning data of learners, and provided effective learning path references for subsequent learners, thus improving the learning experience and effect. Diao et al. [21] proposed a personalized learning path recommendation method based on weak concept mining. First, according to the mastery degree of concepts by history learners, concept maps of different types of learners were generated using the clustering and association rule mining algorithm. Then a set of weak concept learning paths were automatically generated using the topological sorting algorithm. Second, the Long Short-Term Memory based on attention mechanism (LSTM+attention) was trained to predict the learning effect of the learning paths. Finally, the personalized weak concept paths, which met the expected learning effect, were selected from the path prediction results. Cheng [22] proposed a learning path recommendation method based on knowledge graph, which brought personalized course recommendation to students. The online course ontology base was constructed, which achieved the knowledge graph of professional courses, and the graphic database Neo4j was used to store the graph. SpringBoot was used to build a backend system, and a set of course recommendation algorithms were achieved, which filtered learning resources by analyzing the courses taken by students and the learning quality, thus generating a course recommendation list for each student. The system developed based on this method effectively recommended course learning paths to students, and greatly met their learning needs.

Although many learning path recommendation methods of intelligent education have been proposed and implemented, most of them recommend learning paths to target students by relying on the behaviors and preferences of other similar students, instead of taking into consideration individual differences, such as cognitive level and learning style, which may result in unsatisfactory recommendation results. When designing the learning path recommendation method of intelligent education, it is necessary to fully consider the cognitive level of students. CDM provides detailed information on the cognitive ability of students, and helps better understand their learning needs, thus recommending learning paths to them more accurately and effectively. This not only helps improve their learning effect, but also enables more rational utilization of educational resources.

Therefore, this research studied the learning path recommendation method of intelligent education based on cognitive diagnosis. In Chapter 2, this study fully considered the multidimensional features of interaction between students and knowledge when designing the CDM, described the cognitive process, and provided a comprehensive ability modeling method based on cognitive rules. A neural matrix decomposition model was constructed in Chapter 3, which incorporated the personality features of comprehensive ability level, thus obtaining the predicted scores of students in various knowledge and skills. The model consisted of three parts, namely, the generalized matrix decomposition part, the multi-layer perceptron part and the NeuMF layer. Finally, the experimental results verified that the constructed model was effective.

2 CDM FOR LEARNING PATH RECOMMENDATION

Learning behaviors and effect of students are affected by their external features, such as age, gender, cultural background, and learning environment. The key factor affecting the learning effect is their cognitive rules, including learning style, way of thinking, memory ability and so on. Only by comprehensively considering these external features can their learning needs and difficulties be accurately understood, thus providing more effective support for them.

CDM is a highly structured model, which aims to provide a deep understanding of specific skills and knowledge mastery level of students. When designing CDM, it is necessary to consider the multidimensional features of interaction between students and knowledge, including external features and cognitive rules of students, and the results obtained through cognitive diagnosis. These three parts are combined together to form a complete CDM, which provides precise information about cognitive ability of students, thus helping recommend more accurate and personalized learning paths to them.

2.1 Description of cognitive process

Cognitive process was first defined in this study when students learned the learning paths recommended by intelligent education. Let $PG=\{PG_1,PG_2,\ldots,PG_m\}$ be the multidimensional feature sequence generated in the interaction between students and learning projects recommended by intelligent teaching, and $DK_\omega(PG)$ be the corresponding mapping from external features to cognitive rules. CDM construction mainly aimed to not only predict the learning efficiency of students participating in future intelligent education learning, but also speculate on their latent states in learning various knowledge and skills. Let $\Psi_{\beta i}$ be the response function of students in learning projects recommended by intelligent teaching based on cognitive rules, $DK_\omega(\cdot)$ be the mapping functions of different cognitive rules, ω be the cognitive rules and comprehensive ability, s_{ij} be the response of students to the recommended learning projects, and β_i be the latent knowledge mastery state of students.

$$E(s_{ij}=1\mid\beta_i)=\Psi_{\beta_i}(DK_\omega(PG)) \tag{1}$$

$DK_{\omega}(\cdot)$ functions were different for the modeling of different cognitive features. When modeling based on the learning speed of students, knowledge interaction features related to their response time needed to be introduced. Let L be the association features between learning projects recommended by intelligent teaching and knowledge, and I be the interaction features between students and learning projects recommended by intelligent teaching including response time, then there were:

$$DK_{\omega=r} = \Phi(L, I) \tag{2}$$

If memory modeling was based on the learning and forgetting of students, it was necessary to introduce their learning behavior features in intelligent education and the knowledge interaction sequence features related to time interval. Let n be the memory and cognitive rules like learning and forgetting, I be the features of response result interaction between students and learning projects recommended by intelligent teaching, Y be the behavioral features generated in interaction between students and the recommended learning projects, and E be the time interval features in the time series data of interaction between students and the recommended learning projects, then there were:

$$DK_{\omega=n} = \Phi(s_{ij}, Y, E) \tag{3}$$

The latent comprehensive ability of students in learning various knowledge and skills was represented by their internal cognitive rules. Let $DK_{\omega=d}$ be the latent comprehensive ability of students, and $PG_{\omega=d}$ be other cognitive features. The following equation provided the corresponding mapping expression:

$$DK_{\omega=d} = \Phi(DK_{\omega=r}, DK_{\omega=N}, DK_{\omega=p}) \tag{4}$$

The following equation provided the objective function of cognitive diagnosis, which was set based on the comprehensive ability represented by speed, learning, forgetting and other cognitive rules:

$$E(s_{ij} = 1 \mid \beta_i) = \Psi_{\beta_i}(DK_{\omega=d}(PG)) \tag{5}$$

2.2 Comprehensive ability modeling based on cognitive rules

Forgetting is a part of human cognitive process. Students may forget the knowledge and skills that they have learned over time without reviewing and reinforcing them. Therefore, cognitive diagnosis needs to be made regularly to understand their knowledge and skill mastery. In addition, learning paths need to be adjusted based on the results to always match their learning needs and ability. Regular cognitive state diagnosis promptly identifies the learning problems and difficulties of students, and provides effective teaching intervention, thus preventing the continuous development of learning difficulties. Figure 1 shows the cognitive diagnosis principle of students incorporating external features.

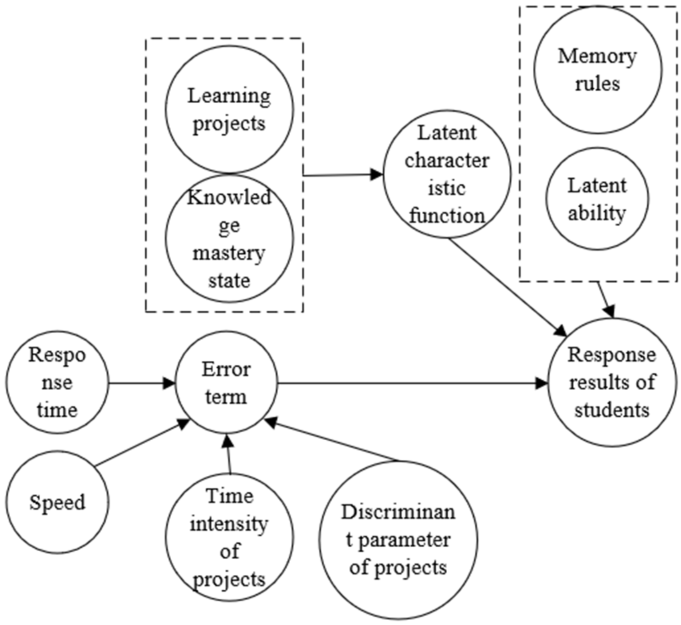

Fig. 1. Cognitive diagnosis principle of students incorporating external features

When students participated in learning projects recommended by intelligent teaching, let n be the cognitive rules including learning and forgetting, g be the forgetting rules, and k be the learning rules, with $n \in \{g,k,\ldots\}$. CDM took into consideration the memory and cognitive rules, which aimed to predict the probability of students mastering knowledge points based on the description their memory and cognitive rules, that is:

$$E(s_{ij} = 1 \mid \beta_i) = \Psi(DK_{\omega=n}(s_{ij}, g, k)) \tag{6}$$

Memory and cognitive rules were mainly influenced by two factors: time features including learning time interval, and learning behavior features including repetitive learning frequency. Therefore, the memory and cognitive rules were represented by the following equation:

$$DK_{\omega=n} = \Phi(s_{ij}, Y, E) \tag{7}$$

Combined with actual situations, the equation of the memory and cognitive rules was further refined as follows:

$$DK_{\omega=n} = \Phi(s_{ij}, Y, E) = \Phi(s_{ij}, \Delta d_o, \Delta r_o, \Delta s_o) \tag{8}$$

CDM took into consideration the learning speed of students, which aimed to describe the learning speed using response time and other features of interaction between students and the recommended learning projects, thus ultimately predicting the probability of knowledge point mastery. Let $L=\{w_j\}$ be the association between the recommended learning projects and knowledge/skills, and $I=\{(s_{11},o_{11}),\ldots,(s_{ij},o_{ij})\}$ be the interactive features of students, then the equation was expressed as follows:

$$E(s_{ij} = 1 \mid \beta_i) = \Psi(DK_{\omega=r}(L, I)) \tag{9}$$

Combined with actual situations, the equation of learning speed rules was further refined as follows:

$$DK_{\omega=r} = \Phi(L, I) = \Phi(l_{ij}, s_{ij}, o_{ij}) \tag{10}$$

The CDM constructed in this study aimed to obtain the entire process features generated in interaction between students and the recommended learning projects. The following equation provided its expression:

$$E(s_{ij} = 1 \mid \beta_i) = \Psi(DK_{\omega=d}(d)) = \Psi(DK_{\omega=r}, DK_{\omega=g}, DK_{\omega=k}) \tag{11}$$

The following equations provided the mapping function expressions of the speed, learning, and forgetting of students:

$$\begin{aligned} DK_{\omega=r} &= \Phi(L, I) \\ DK_{\omega=g} &= \Phi(L, E) \\ DK_{\omega=k} &= \Phi(L, Y) \end{aligned} \tag{12}$$

3 LEARNING PATH RECOMMENDATION OF INTELLIGENT EDUCATION BASED ON COGNITIVE DIAGNOSIS

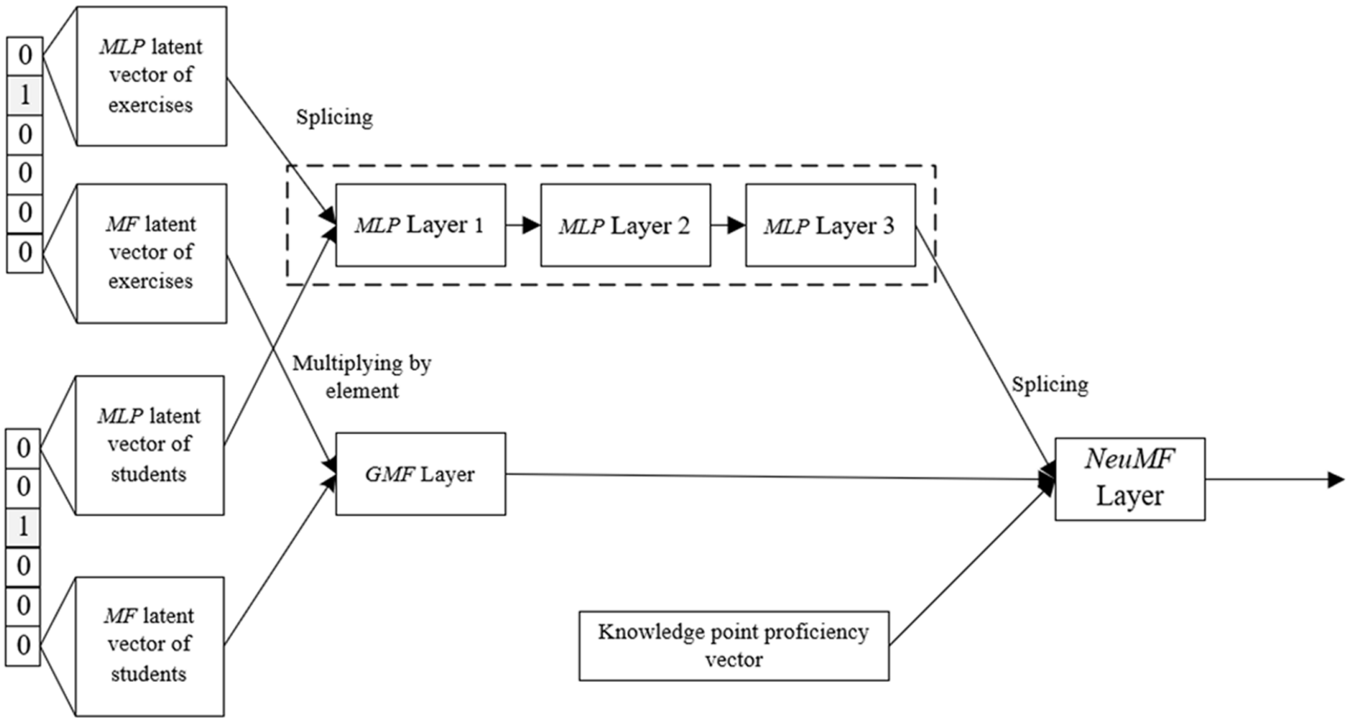

Fig. 2. Architecture of the constructed recommendation model

The CDM constructed in the previous section was used to model the intelligent education learning process of students, which obtained the personality features of their comprehensive ability level based on cognitive rules. In order to fully consider the nonlinear features of interactive fitting between students and the recommended learning projects, this study constructed a neural matrix decomposition model, which incorporated the personality features based on cognitive rules, in order to obtain the predicted scores of students in learning various knowledge and skills. The model consisted of three parts, namely, the generalized matrix decomposition part, the multi-layer perceptron part and the NeuMF layer. Figure 2 shows the architecture of the constructed model. Finally, according to the actual needs and cognitive level of students, this study set the difficulty range of recommending learning projects recommended by intelligent teaching, thus recommending the recommended topK learning projects within the difficulty range to students.

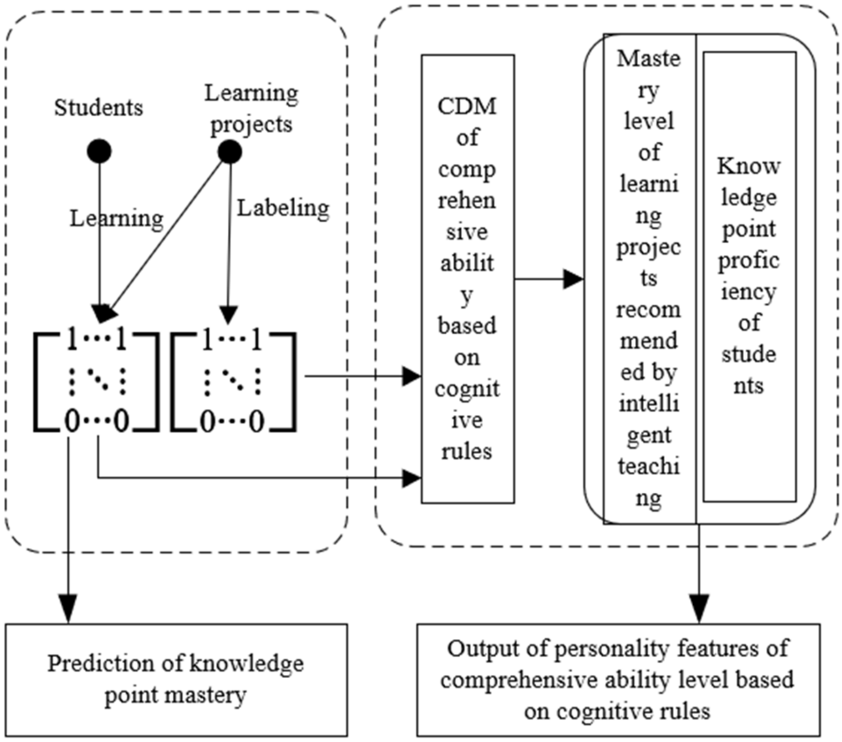

Fig. 3. CDM workflow

Figure 3 shows the CDM workflow. Let X be the knowledge point mastery degree matrix of all students, Y be the mastery level matrix of learning projects recommended by intelligent teaching, β_{vj} be the mastery degree of knowledge point j by student v, with $\beta_{vj} \in [0,1]$, β_v be the knowledge point proficiency vector, y_{vu} be the mastery level of the recommended learning project u by student v, with $y_{vu} \in [0,1]$, V be the number of students, U be the number of learning projects recommended by intelligent teaching, and J be the number of knowledge points, then the specific expressions of X and Y were given by the following equations:

$$X = [x_1, x_2, \ldots, x_V]^T = \begin{bmatrix} \beta_{11} & \beta_{12} & \cdots & \beta_{1J} \\ \beta_{21} & \beta_{22} & \cdots & \beta_{2J} \\ \vdots & \vdots & & \vdots \\ \beta_{V1} & \beta_{V2} & \cdots & \beta_{VJ} \end{bmatrix} \tag{13}$$

$$Y = \begin{bmatrix} y_{11} & y_{12} & \cdots & y_{1J} \\ y_{21} & y_{22} & \cdots & y_{2J} \\ \vdots & \vdots & & \vdots \\ y_{V1} & y_{V2} & \cdots & y_{VJ} \end{bmatrix} \tag{14}$$

The mean value was further calculated for each row of Y, which obtained the personality features of comprehensive ability level of each student based on cognitive rules. Let c_v be the overall knowledge level difference among different students, and y_{vu} be the average value of the v-th row in Y, then there were:

$$c_v = \frac{\sum_{u=1}^{U} y_{vu}}{U} \tag{15}$$

The diagnostic results were applied to predict the knowledge point mastery of students, that is, to predict the probability of students correctly answering the learning projects. The NeuMF layer of the constructed model incorporated the personality features into the input and output of the model, which improved the effect and interpretability of learning path recommendation.

In the generalized matrix decomposition part, this study set up a linear kernel to simulate the interaction between latent features. Let a_v be the one-hot encoding vector of students, c_u be the one-hot encoding vector of recommended learning projects, E_v^H be the latent vector of students in the generalized matrix decomposition part, and w_u^H be the latent vector of recommended learning projects. After inputting a_v and c_u into the embedding layer, E_v^H and w_u^H were obtained and then input into the generalized matrix decomposition layer. Let $e_v^H \in [0,1]^{1\times M}$ and $w_u^H \in [0,1]^{1\times M}$, and * be the multiplication of vectors by element, then the equation was as follows:

$$\Psi^{GMF} = e_v^H * w_u^H \tag{16}$$

Similarly, in the multi-layer perceptron part, after inputting a_v and c_u into the embedding layer of the multi-layer perceptron, e_v^N and w_u^N were obtained and then input into the two full connection layers. Let $e_v^N \in [0,k]^{1\times k}$ and $w_u^N \in [0,k]^{1\times k}$; Q_1, Q_2 and Q_3 be the weights of the neural network; y_1, y_2 and y_3 be the biases of the neural network; g be the ReLU activation function. The specific definitions were as follows:

$$\Psi_1^{MLP} = g\left(Q_1^T \begin{bmatrix} e_v^N \\ w_v^N \end{bmatrix} + y_1\right) \tag{17}$$

$$\Psi_2^{MLP} = g(Q_2^T \Psi_2^{MLP} + y_2) \tag{18}$$

$$\Psi_3^{MLP} = g(Q_3^T \Psi_2^{MLP} + y_3) \tag{19}$$

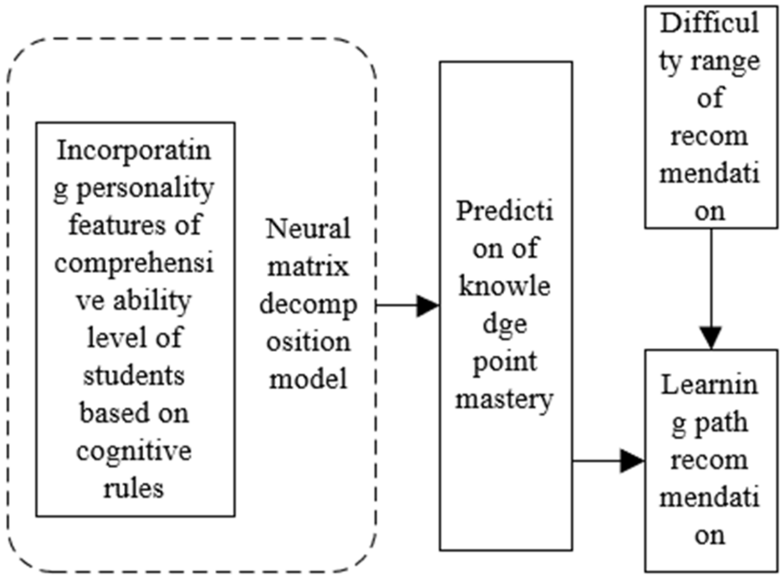

Fig. 4. Process of obtaining predicted scores in learning various knowledge and skills

This study spliced β_v with the hidden layer output of the last layer in the generalized matrix decomposition part and the multi-layer perceptron part, and the splicing operation results were used as the input of the NeuMF layer, which obtained the predicted scores b'_{vu}. Let f be the weight of the neural network, ε be the sigmoid activation function, β_v=[β_{v1},β_{v2},...,β_{vj}] be the knowledge point mastery of students, and β_{vj} be the mastery degree of knowledge point j by student v, with $\beta_{vj} \in [0,1]$. The specific calculation equation was as follows:

$$b'_{vu} = \varepsilon\left(f^T\begin{pmatrix}\Psi^{GMF}\\ \Psi_3^{MLP}\\ \beta_v\end{pmatrix}\right) \tag{20}$$

The predicted scores of students in learning various knowledge and skills were further calculated using the following equation:

$$b = \delta \times c_v + (1-\delta)b'_{vu} \tag{21}$$

where, δ was used to adjust the proportion of the personality features c_v. Figure 4 shows the process of obtaining predicted scores of various knowledge and skills learned.

The following model loss function was constructed, based on the cross entropy between the output b and the real label s:

$$LOSS = -\sum_i (s_i \log b_i + (1-s_i)\log(1-b_i)) \tag{22}$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

Figure 5 shows the knowledge point mastery of each student. It can be seen from the figure that most students have a good grasp of all knowledge points, because their scores in each knowledge point are 12, indicating that they have fully mastered these knowledge points. However, some students have shortcomings in mastering specific knowledge points. For example, Students 4 and 9 have 0 scores in Knowledge point 6, indicating that they have not mastered this knowledge point. In addition, Student 4 has 0 scores in Knowledge point 9, indicating that the student has mastered neither of the two knowledge points. In summary, it can be seen that some students still have shortcomings in certain knowledge points, though most students have a good grasp of various knowledge points, indicating the importance of recommending personalized learning paths. The most suitable learning path should be provided according to the specific situations of each student, thus improving his/her learning efficiency and effect.

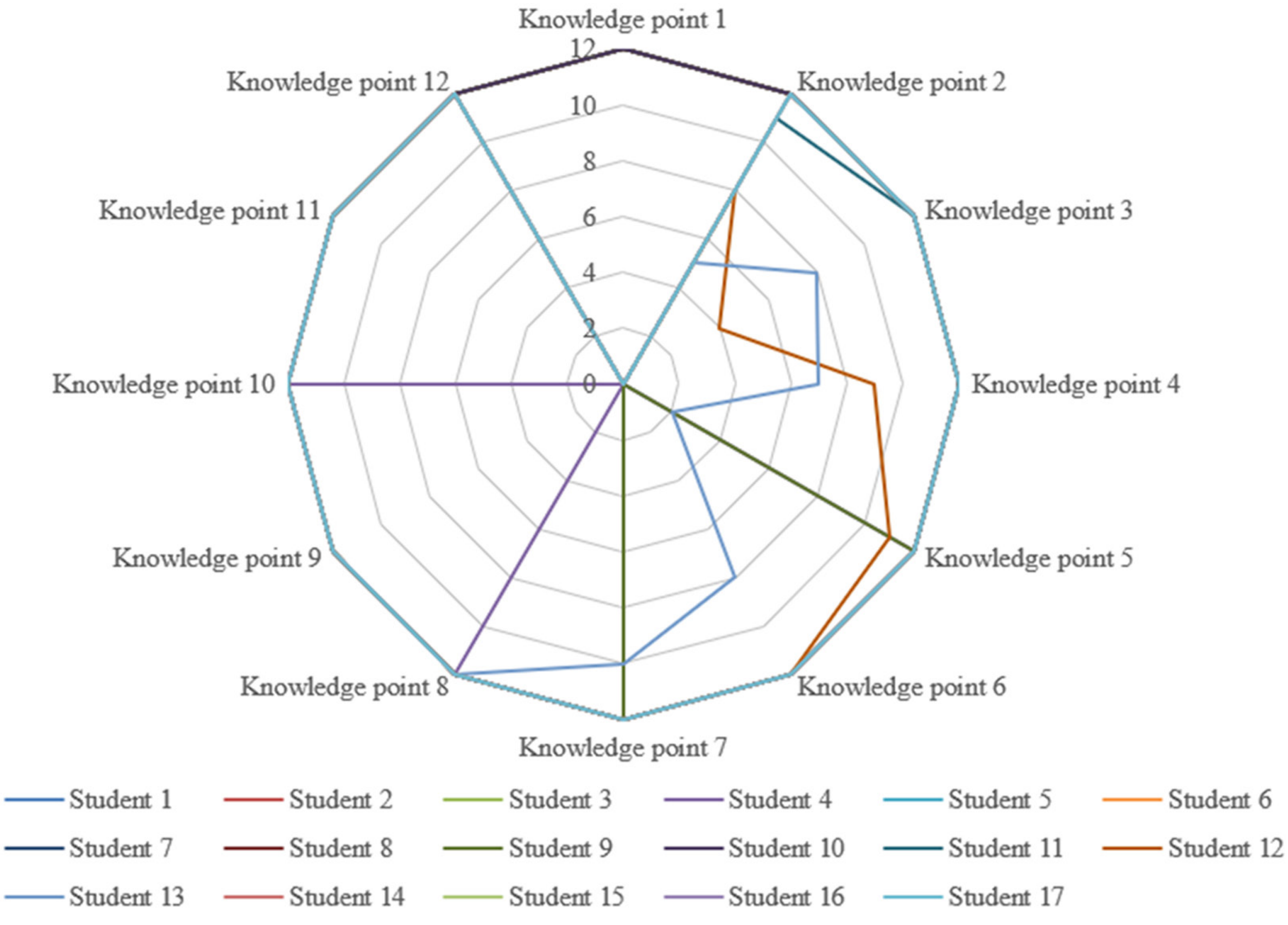

Fig. 5. Knowledge point mastery of students

Table 1. Accuracy comparison of different CDMs

Model	Error		Accuracy	
	MAE	RMSE	ACC	AUC
AHM	0.352	0.695	0.638	0.695
RSM	0.341	0.574	0.614	0.741
DINA	0.269	0.415	0.748	0.738
Model in this study	0.274	0.484	0.801	0.869

Table 1 presents the accuracy comparison results of different CDMs. Performance indicators of four CDMs can be seen from the the table, namely, the attribute hierarchical model (AHM), the rule space model (RSM), the DINA model, and the model proposed in this study. Indicators include mean absolute error (MAE), root mean square error (RMSE), accuracy (ACC) and area under curve (AUC). In this table, the DINA model and the model in this study have relatively small MAE values, indicating that the two models have relatively small prediction errors. The DINA model has the smallest RMSE, which is followed by the model in this study. The model in this study has the highest ACC, which is followed by the DINA model. The model in this study has the highest AUC value, indicating that it outperforms other three models in classification performance. It was concluded that the model proposed in this study outperformed the AHM, the RSM, and the DINA model in terms of diagnostic accuracy, especially accuracy and classification performance.

After recommending intelligent education learning paths to students based on cognitive diagnosis, Figure 6 shows their error and guess rates in answering recommended learning projects. Guess rate represents the likelihood of randomly guessing in the project, while error rate represents the probability of answering incorrectly in the project. Most projects, such as Projects 1 to 10, 12, 13, 15, etc., have relatively low guess and error rates, meaning that students have good performance in these projects and are able to understand and master relevant knowledge, with random guesses or incorrect answers in few cases. This is a positive sign for teaching, indicating that teaching methods and contents may be effective. Although Projects 21, 25, and 26 have a high guess rate, the error rate is relatively low, maybe indicating that the questions in these projects are more intuitive or easy to guess. However, attention should be paid to this, because a high guess rate may mean that students have not fully understood these knowledge points. Overall, the guess and error rates of most projects are low, indicating that the teaching process may be effective. However, some projects require attention and intervention of teachers, especially those with high guess and error rates, which may require teaching strategy adjustment or increased guidance for these knowledge points.

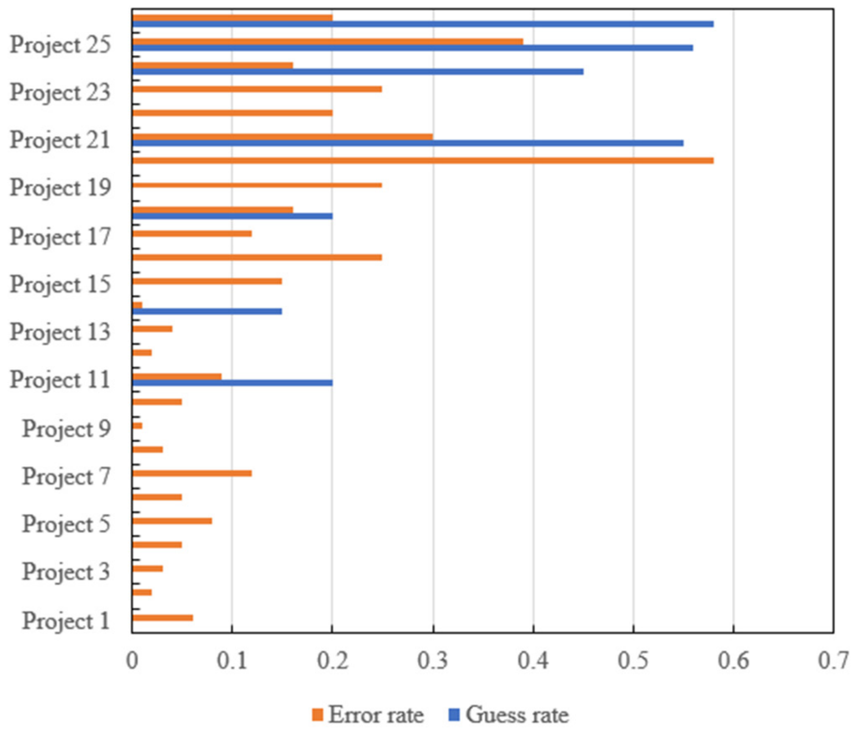

Fig. 6. Error and guess rates of students in answering questions

Table 2. F1 values of recommendation effect of difficult learning paths using different methods

Difficulty Degree	Model	Proportion of the Validation Set (%)		
		40	50	60
Difficult	CF	0.4215	0.3014	0.3417
	KG	0.4674	0.4852	0.4152
	CB	0.4629	0.4619	0.4629
	DL	0.4013	0.4385	0.4052
	SRM	0.5814	0.5172	0.5341
	Model in this study	0.6926	0.6821	0.6817

Table 2 shows the F1 values of recommendation effect of difficult learning paths using different learning path recommendation models in different proportions of validation set. Similarly, the F1 value of the model proposed in this study exceeds that of other models in difficult learning path recommendation, indicating that the model has high accuracy and recall in prediction effect, and is particularly effective in recommending difficult learning paths. In practical applications, this model can help recommend difficult learning paths more accurately, thus improving learning efficiency and effect.

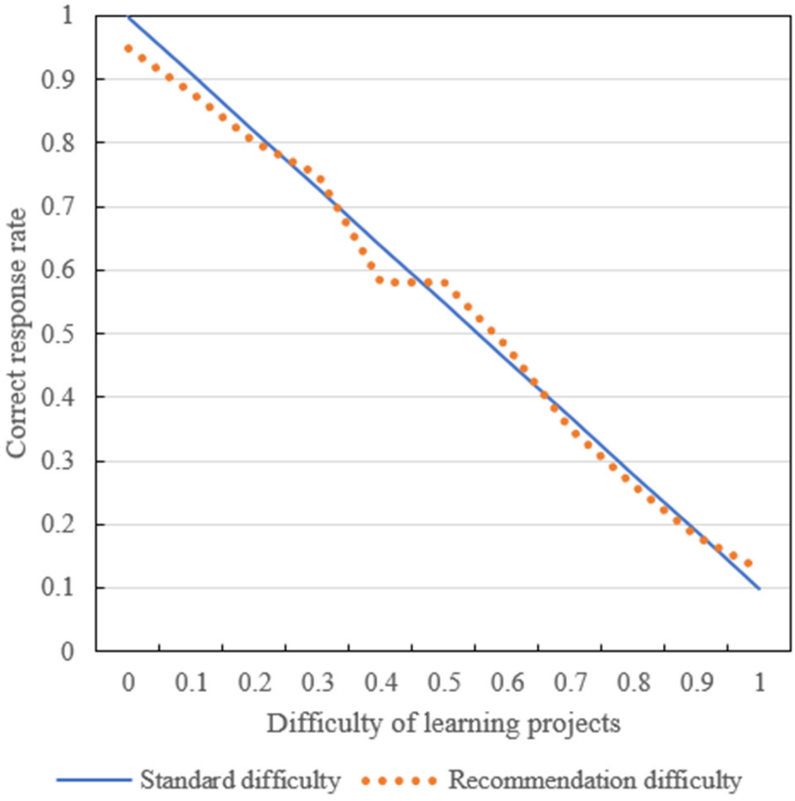

Fig. 7. Impact of difficulty on the learning project recommendation results

Figure 7 shows the correct response rates of learning projects with different difficulty degrees, i.e., standard and recommendation difficulty. It can be seen that the correct response rate shows a significant downward trend as the difficulty of projects with standard difficulty increases, which is in line with general cognitive rules, because higher difficulty often requires higher levels of knowledge and skills, leading to relatively low likelihood of correct responses. The correct response rate also decreases as the difficulty of projects with recommendation difficulty increases. However, the correct response rate remains at 0.58 when the difficulty degrees are 0.4 and 0.5, indicating that the recommendation difficulty may have appropriately considered the learning level of students, which prevents the correct response rate from further decreasing. Overall, the correct response rate shows a decreasing trend as the difficulty of learning projects with both standard and recommendation difficulty increases, but the correct response rate of learning projects with recommendation difficulty has increased compared with that with standard difficulty, indicating that the learning path recommendation system has optimized the learning paths based on cognitive level of students and project difficulty, thus improving their learning efficiency and effect.

It was concluded from the above results that the difficulty degree had a significant impact on the recommendation results of learning projects. Reasonable recommendation difficulty enabled students to still maintain a certain correct response rate and improve their learning efficiency and effect when facing learning projects with higher difficulty degree. At the same time, learning projects with appropriate difficulty were recommended to students based on their cognitive ability and preferences, which made the learning process more in line with their personalized needs, thus improving their learning satisfaction.

5 CONCLUSION

A learning path recommendation method of intelligent education was proposed in this study based on cognitive diagnosis. Personalized and accurate learning paths were recommended to students by combining with CDM. This study fully considered the multidimensional features of interaction between students and knowledge when designing the CDM, described the cognitive process, and provided a comprehensive ability modeling method based on cognitive rules. A neural matrix decomposition model was constructed, which incorporated the personality features of students based on cognitive rules, thus obtaining the predicted scores of students in learning various knowledge and skills. The model consisted of three parts, namely, the generalized matrix decomposition part, the multi-layer perceptron part and the NeuMF layer. Combined with the analysis results of knowledge point mastery of students, the accuracy of different CDMs was compared. The results showed that the model proposed in this study outperformed the AHM, the RSM, and the DINA model in terms of diagnostic accuracy, especially accuracy and classification performance. The cognitive diagnosis results and the response error and guess rates of students were provided and analyzed. Then the study gave the F1 values of recommendation effect of easy and difficult learning paths using different learning path recommendation models in different proportions of validation set. It was verified that the model constructed in this study helped recommend difficult learning paths more accurately in practical applications, thus improving learning efficiency and effect. Finally, after analyzing the correct response rates of learning projects with both standard and recommendation difficulty, it was concluded that recommendation of learning projects with appropriate difficulty based on the cognitive ability and preferences of students made the learning process more tailored to their personalized needs.

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