Use of a Deep Learning Approach for the Evaluation of Students' Online Learning Cognitive Ability

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Lili Zhao(✉)
Department of Student Work and Social Sciences, Shijiazhuang University of Applied Technology, Shijiazhuang, China
2005110229@sjzpt.edu.cn

Abstract—The cognitive ability evaluation of college students' online learning still faces many challenges. Evaluation of college students' online learning cognitive ability is helpful to monitor the learning effect and progress of students, so as to detect problems in time, make suggestions and take corresponding measures to improve. However, the existing evaluation methods for the cognitive ability of college students' online learning often only focus on the degree of knowledge mastery of students, while ignoring the performance of students' learning strategies, autonomous learning ability and emotional attitude in the online learning process. And it is often impossible to understand the learning status of students in real time. To this end, this article studies the evaluation method of college students' online learning cognitive ability based on deep learning. The evaluation of online learning cognitive ability of college students is divided into two parts: online learning ability evaluation and learning recursive ability evaluation. By introducing the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network and constructing the corresponding evaluation model, it's better to evaluate the online learning cognitive ability of college students. Based on the historical learning behavior data of students in the online learning process, the online learning cognitive state is predicted, and the performance of the model is further improved through data enhancement and self-attention mechanism. Experimental results verify the validity of the constructed model.

Keywords—deep learning, college students' online learning, cognitive ability evaluation

1 Introduction

With the development of technology and the popularization of the Internet, online learning has become the main learning method for more and more college students. Especially under the background of the COVID-19, most higher education institutions are forced to conduct distance teaching [1–5]. However, although the advantages and convenience of online learning have been widely recognized, there are still many challenges in the cognitive ability evaluation of online learning for college students.

Evaluation of college students' online learning cognitive ability is helpful to monitor the learning effect and progress of students, so as to detect problems in time, make suggestions and take corresponding measures to improve [6–11]. By evaluating the cognitive ability of college students in online learning, it is possible to better understand the individual features of students, provide teachers with personalized teaching suggestions, and promote the development of students. Cognitive ability evaluation can provide course designers with information about students' learning needs and difficulties, so as to optimize course design and improve teaching quality [12–19]. The research on evaluation of college students' online learning cognitive ability will help enrich and develop the theoretical system of online learning evaluation. The research results can provide a scientific basis for online learning cognitive ability evaluation and provide reference for relevant policy makers and education administrative departments.

Rohaeti et al. [20] analyzes the relationship between students' mathematical understanding, reasoning ability and cognitive stage. This study is a descriptive analysis study involving 414 eleventh grade students (aged 17.43) from seven high schools. The tools used are the Mathematical Comprehension and Reasoning Ability Test, the Longest Test and the Logical Thinking Test. According to the research, these findings have two properties. First, according to the age of the subjects (17.43 years old), Piaget's theory has different findings on the cognitive stage of the students, there are many students who have not reached the formal operational stage, that's, 21% of the students are still in the concrete stage, 34% of the students are still in the transition stage, and only 45% of the students are in the formal stage. Learning preferences are indirectly related to student success in engineering courses, but there is not a lot of research linking learning preferences to cognitive ability. A better understanding of the relationship between learning styles and cognitive abilities will allow educators to optimize the classroom experience for students. Hames and Baker [21] aims to determine whether there is a relationship between the learning styles of students identified by the Felder Soloman Scale of Learning Styles (FSILS) and their cognitive performance. Three tests are used to evaluate students' cognitive abilities: a matrix reasoning task, a Tower of London task, and a mental rotation task. Results are quantified using statistical t-tests and correlation coefficients. Lee et al. [22] aims to understand the status quo of students' metacognition, and their attitudes towards problem-solving ability, and explore the relationship between the two. Using descriptive statistics, t-test, Pearson product-moment correlation, and regression analyses, there wis a moderate correlation between subjects' metacognition and problem-solving ability ($r = .531$, $p < .05^*$). Through simple regression analysis, metacognition is found to have significant predictive power for problem-solving ability. Williams et al. [23] presents the preliminary results of the first phase of a longitudinal study on design cognition and the impact of design education on design practice. It aims to monitor the development of engineering design thinking through a three-year protocol study of control and experimental groups of engineering students. Drawing on innovations in cognitive science, including ontology-based protocol encoding and novel protocol analysis methods, the study is designed to characterize students' cognitive development, identify differences over time, and relate these differences to students' educational experiences.

Through sorting out and summarizing, it is found that the existing evaluation methods of online learning cognitive ability of college students often only focus on the degree of knowledge mastery of students, while ignoring the performance of students' learning strategies, autonomous learning ability and emotional attitude in the online learning process. Moreover, it is often impossible to understand the learning status of students in real time, and it is difficult to find out the problems of students in the learning process and intervene in time. To this end, this article introduces a deep learning model and conducts research on the evaluation method of online learning cognitive ability of college students based on deep learning. The article first divides the evaluation of college students' online learning cognitive ability of into two parts in the second chapter: online learning ability evaluation and learning recursive ability evaluation. By introducing the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network and constructing the corresponding evaluation model, it's better to evaluate the online learning cognitive ability of college students. In the third chapter, based on the historical learning behavior data of students in the online learning process, the article predicts their online learning cognitive state, and further improves the performance of the model through data enhancement and self-attention mechanism. Experimental results verify the validity of the constructed model.

2 Evaluation of students' online learning ability and learning recursive ability

Each student has different learning ability, and their ability to understand and accept knowledge is different. Moreover, the learning process is a process with certain recursive features. In this process, students gradually accumulate knowledge, improve their skills, and increase their experience. Therefore, the individual differences of students should be considered when evaluating college students' online learning cognitive ability and also making full use of the sequence dependence among the historical information data of students' learning. This article divides the evaluation of college students' online learning cognitive ability into two parts: online learning ability evaluation and learning recursive ability evaluation. By introducing the learning ability layer and the learning recursive ability layer into the *Dynamic Key-Value Memory Networks* (*DKVMN*), and constructing the corresponding evaluation model, it's better to evaluate the online learning cognitive ability of college students.

DKVMN is a deep learning model based on memory network, which has strong time series information processing and representation learning capabilities. The introduction of learning ability layer and learning recursive ability layer helps to better capture the individual differences of students and the recursive features in the learning process. The model is also very interpretable, and it is relatively easy to visualize the internal structure and workings of the model. This helps teachers and students understand the basis of the evaluation results and provide a reference for improving learning methods.

The learning ability layer focuses on the individual differences in students' ability to understand and accept knowledge, and helps to reveal the strengths and weaknesses of students in different areas of knowledge. The learning recursive ability layer focuses on the recursive features of knowledge accumulation and experience growth in the learning process, which helps to analyze the growth trend of students in the learning process. Figure 1 shows the structure diagram of the constructed evaluation model.

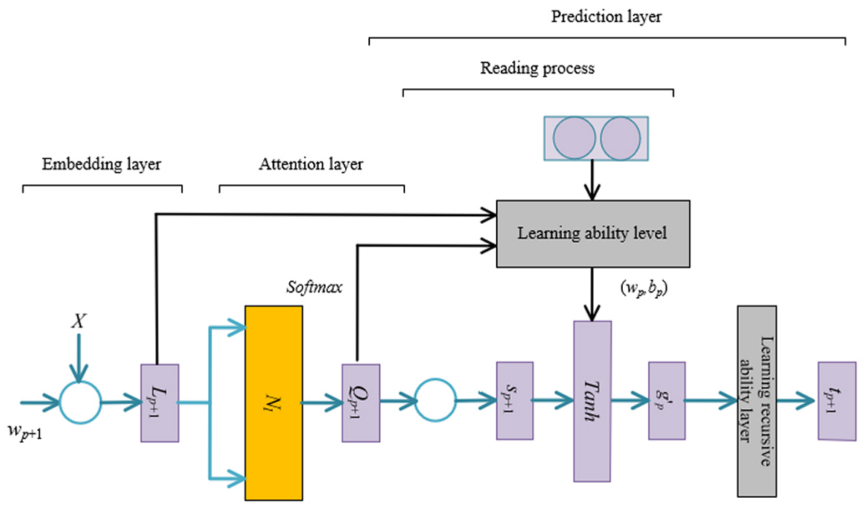

Fig. 1. Structural diagram of the constructed evaluation model

2.1 Learning ability layer

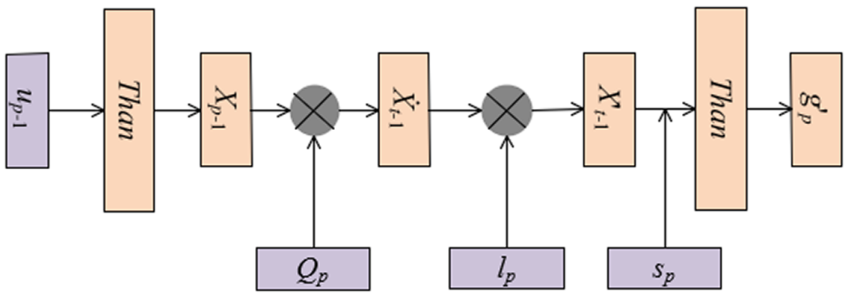

Fig. 2. Learning ability layer architecture

Students' online learning ability can be distinguished from the dimensions of metacognitive ability, emotional attitude, and knowledge application proficiency. The learning ability layer is designed under the guidance of this theory. Figure 2 shows the learning capability layer architecture.

Because the answer sequence can reflect the dynamic changes of students in the learning process, including the progress of knowledge mastery and the adjustment of learning strategies. Moreover, different students may adopt different problem-solving methods and learning strategies when facing problems. Through the analysis of the answer sequence, it's possible to explore the strategies and methods used by students in the process of solving problems, so as to further understand the individual differences of students. So fully exploring the features of online learning ability that the student's answer sequence ($A = \{a_1, a_2, a_3 \dots a_p\}$, $a_p = (w_p, b_p)$) implies can further distinguish the individual differences of students' online learning ability.

This article builds a fully connected neural network layer $A = \{a_1, a_2, a_3 \dots a_p\}$ to extract the features of students' online learning ability. Assuming that the subject ability shown by the students in the previous $p-1$ learning is represented by X_{p-1}, the embedding vector of the answer sequence A_{p-1} is represented by u_{p-1}, and the weight matrix and bias vector of the fully connected layer are respectively represented by Q_X and y_X, the expression is given by:

$$X_{p-1} = \mathrm{Tanh}(Q_X^T u_{p-1} + y_X) \tag{1}$$

Use the relevant weight matrix q_t to describe the relationship between the students' online learning ability and the knowledge points involved in the topic, which to a certain extent characterizes the students' metacognitive ability:

$$X_{p-1} = q_p(i) * X_{p-1} \tag{2}$$

Calculate the relationship between the student's online learning ability and the input vector this time, which is used to represent the student's ability to apply the knowledge points learned, that's, the student's knowledge application proficiency

$$X'_{p-1} = X_{p-1} * l_p \tag{3}$$

Further, the students' ability to learn knowledge points is combined with the relevant learning cognitive state s_p read from the value memory matrix N_p^u, and the combined result is input into the fully connected layer to form a new joint vector g_p'. The specific process is given by:

$$g_p' = \mathrm{Tanh}(Q_g^T [s_p, X'_{p-1}] + \phi_g) \tag{4}$$

It can be seen from the above process that the constructed model has fully considered the differences in students' online learning abilities when evaluating students' online learning cognitive abilities.

2.2 Learning recursive ability layer

Many studies have proved that *Long Short-Term Memory* (*LSTM*) network and *Gated Recurrent Unit* (*GRU*) network have superior performance in processing time series data (such as language model and time series prediction). Therefore, there is strong theoretical support for adopting these models in the field of evaluation of students' recursive learning ability. In order to better mine the rules of knowledge accumulation and experience growth in the students' learning history information, this article builds a learning recursive ability layer based on *LSTM* and *GRU* networks to process the students' practice data and evaluate the learning recursive ability.

Inputting the joint vector g'_p which contains information such as students' meta-cognitive ability, emotional attitude and knowledge application proficiency into *LSTM* may realize the extraction of pre and post correlation features of this information, and use the extracted features to make decisions on the current learning. Assume that the forget gate is represented by h_p, the input gate is represented by i_p, the output gate is represented by e_p, the unit state is represented by d_p, and the hidden state is represented by f_p. The following formula gives the specific process expression:

$$h_p = Sigmoid(Q_h \cdot [f_{p-1}, g'_p] + \phi_h) \tag{5}$$

$$i_p = Sigmoid(Q_i \cdot [f_{p-1}, g'_p] + \phi_i) \tag{6}$$

$$e_p = Sigmoid(Q_e \cdot [f_{p-1}, g'_p] + \phi_e) \tag{7}$$

$$\tilde{d}_p = Than(Q_d \cdot [f_{p-1}, g'_p] + \phi_d) \tag{8}$$

$$d_p = h_p * d_{p-1} + i_p * \tilde{d}_p \tag{9}$$

$$f_p = e_p * Than(d_p) \tag{10}$$

Assuming that the model predicts that the probability of students answering $wp_{correctly}$ is represented by t_p, f_p *is* input into the fully connected layer to realize the prediction of *students*' online answering *performance:*

$$t_p = Sigmoid(Q_t^T f_p + \phi_t) \tag{11}$$

Inputting g'_p into *the GRU* network, assuming that the update gate is represented by c_p, the reset gate is represented by s_p and the output hidden vector is represented by f_p, then the specific calculation process is as follows:

$$s_p = Sigmoid(Q_s \cdot [f_{p-1}, g'_p]) \tag{12}$$

$$c_p = Sigmoid(Q_c \cdot [f_{p-1}, g'_p]) \tag{13}$$

$$f_p = Than(Q_f \cdot [s_p * f_{p-1}, g'_p]) \tag{14}$$

$$f_p = (1 - c_t) * f_{p-1} + c_p * f_p \tag{15}$$

Inputting f_p into the fully connected layer to realize the prediction of students' online answering performance:

$$t_p = Sigmoid(Q_t^T f_p + \phi_t) \tag{16}$$

Assuming that the predicted value of online answering performance is represented by t_p, and the actual online answering performance is represented by b_p, the parameters of the constructed model are optimized by minimizing the standard cross-entropy loss function between t_p and b_p, namely:

$$LOSS = -\sum (b_p \log t_p + (1-b_p)(1-\log t_p)) \tag{17}$$

3 Prediction of students' online learning cognitive state

Through prediction of online learning cognitive state, teachers and students can understand the cognitive state of students in the learning process in real time, so as to take corresponding measures in a more timely manner and improve the learning effect. At the same time, it can detect the learning difficulties that students may encounter in time, help teachers understand students' acceptance and needs of different learning resources, enable teachers to take early intervention measures before problems occur, adjust and optimize learning resources, and reduce risk of setbacks that students meet in online learning and improve the quality of online learning.

This article predicts students' online learning cognitive state based on their historical learning behavior data during the online learning process. Due to the potential imbalance in student learning behavior data in online learning, some types of behavior data may be more abundant than others. Through data augmentation, this imbalance can be alleviated to a certain extent, and the ability of the model to identify and predict different types of learning behaviors can be improved. At the same time, data augmentation can expand the diversity of training data sets and help improve the generalization ability of the model. This means that the model is more stable when dealing with unseen data, which improves the accuracy of cognitive state prediction in online learning. Figure 3 presents the prediction model framework.

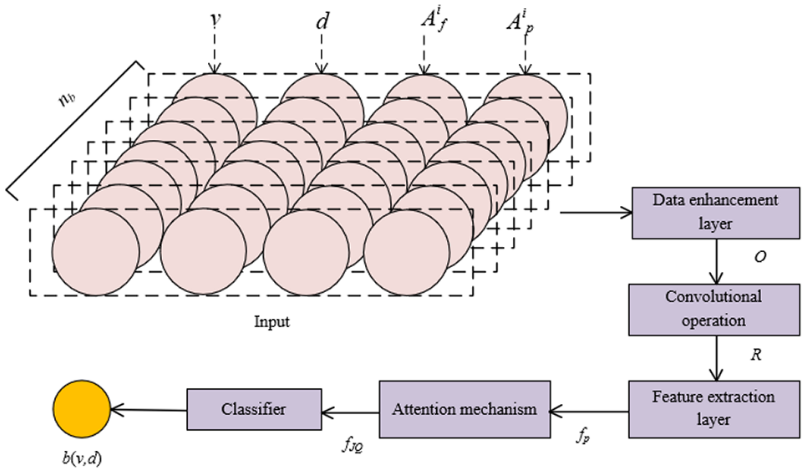

Fig. 3. Prediction model framework

For the *i*-th learning activity feature in the *p*-th video learning activity, extend the student information *p*, course information *d*, and the *i*-th feature's historical learning activity $a_f^i(v,d)$ to the *p*-th video learning activity for data augmentation:

$$\hat{a}^i = [v \oplus d \oplus a_f^i(v,d) \oplus a_p^i(v,d)] \tag{18}$$

In the above formula, $1 \le i \le n_a$, $\hat{a}^i \in R^{nd}$ and the *i*-th feature's historical learning activity is obtained by the mapping function H: $A_f^i \to [avg\ (\{a^i_h\}),\ max\ (\{a^i_h\}),\ \ldots]$ $(1 \le h \le p{-}1)$. So $\hat{A} = \hat{A}^1 \oplus \hat{A}^2 \oplus \ldots \oplus A_{na}\hat{a} \in \hat{A}$, $\hat{a} \in R^{nd\times na}$. Subsequently, $\hat{A}^i$ is passed through an embedding layer to convert each *a* into a dense vector. The corresponding embedding vector is obtained by multiplying ${}^{i}\hat{A}^i$ by the parameter vector $q_o \in R^{nd}$:

$$O^i = \hat{A}^i \cdot q_o \tag{19}$$

The above formula uses $O^i \in R^{nd\times no}$ represents the embedding matrix of $\hat{A}^i$. Here, $O \in R^{ndna\times no}$ can be seen as a data-augmented representation of students' online learning process behavior data.

Further, the constructed prediction model uses convolutional neural network and gated recurrent unit to extract the feature information of students' online learning behavior. Use a one-dimensional convolutional neural network to perform convolution operations on $O^i(k \le i \le n_a)$:

$$R^i = \varepsilon(Q_{conv}\xi(O^i) + \phi_{conv}) \tag{20}$$

In the above formula, $Q_{conv} \in R^{nconv\times ncme}$, $\varphi_{conv} \in R^{mconv}$, the activation function is represented by $\varepsilon(\cdot)$, $\xi()$ is the function used to flatten O^i into a one-dimensional vector.

Let the vector after convolution of O^i and O is represented respectively by $R^i \in S^{mconv}$ and $R\ S^{nconv \times na}$, the update gated output and reset gated output are represented by s_p and $c_p \in R^{na \times nf}$ respectively, and the derivable variable parameters are represented by Q_s, Q_c, $Q_f \in R^{conv \times nf}$, V_s, V_c, $V_f \in R^{nf \times nf}$, φ_s, φ_c and $\varphi_f \in R^{nf}$. Then:

$$s_p = \varepsilon(R_p^T Q_s + f_{p-1} V_s + \phi_s) \tag{21}$$

$$c_p = \varepsilon(R_p^T Q_c + f_{p-1} V_c + \phi_c) \tag{22}$$

$$\tilde{f}_p = \tanh(R_p^T Q_f + (s_p \otimes f_{p-1})) V_f + \phi_f \tag{23}$$

$$f_p = c_p \otimes f_{p-1} + (1\text{-}c_p)\tilde{f}_p \tag{24}$$

The self-attention mechanism can assign different weights to each feature, thereby strengthening the key features closely related to the learned cognitive state. This helps to improve the effectiveness of feature extraction, thereby improving the accuracy of learning cognitive state prediction. At the same time, it can capture the long-distance dependencies in the learning behavior sequence, so as to reveal the development trend of students in the learning process. This is of great significance for analyzing students' learning rules and predicting learning cognitive state. In order to further improve the performance of the model, this model uses the self-attention mechanism to carry out feature weighting on the extracted features of students' online learning behavior. The extracted feature information of students' online learning behavior is used as input, and the assumed parameters are composed of Q_W, Q_L and $Q_U \in R^{nf \times nx}$, the weighted feature f_{JQ} can be obtained:

$$f_{JQ} = soft\max\left(\frac{(f_p Q_W)(f_p Q_l)^T}{\sqrt{n_a}}\right)(f_p Q_u) \tag{25}$$

And $f_{JQ} \in R^{nr \times nx}$ can be directly classified by the classifier, so this article is based on $\xi(\cdot)$ to convert f_{JQ} into a one-dimensional vector, and then process it based on *the sigmoid* () function to complete the calculation of the cognitive state of students' online learning. Assuming that the parameters are represented by Q_r and the model prediction results are represented by $\hat{b}(v,d) \in [0,1]$, then:

$$\hat{b}(v,d) = \frac{1}{1+\exp(-q_r \xi(f_{Atten}))} \tag{26}$$

Finally, *the Adam* optimizer optimizes the model parameters, assuming that the set of all (*v, d*) is represented by *Y*, and in the actual situation, the online learning cognitive state of student v in course d is represented by b (v, d), then the constructed minimized cross-entropy loss function can be expressed by the following formula:

$$LOSS(\Psi) = \sum_{(v,d)\in Y} [b(v,d)\log(\hat{b}(v,d)) + (1-b(v,d))\log(1-\hat{b}(v,d))] \tag{27}$$

4 Experimental results and analysis

In order to verify the validity of the model constructed herein, this article designs a comparative experiment. Two sample sets for experiments are constructed. Sample set 1 involves a total of 120 knowledge points, with 5,210 students participated in online answering, and 4,512,374 online answering behavior records generated. Sample set 1 involves a total of 130 knowledge concepts, with 4,467 students participated in online answering, and 336,212 online answering behavior records generated.

Table 1 shows the *AUC* value of the improvement effect of different improvement strategies on the model. It can be seen from the table that in the experiment of sample set 1, the average *AUC* of the traditional dynamic key-value memory network is 82.38%, and the highest value is 82.51%; the average *AUC* value of the model with only the learning ability layer is 82.50%, and the highest value is 82.57%; the average value of this model is 82.65%, and the highest value is 82.76%. In the experiment of sample set 2, the average *AUC* of the traditional dynamic key-value memory network is 74.49%, and the highest value is 74.70%; the average *AUC* value of the model with only the learning ability layer is 74.65%, and the highest value is 74.75%; the average value of this model is 74.68% and the highest value is 74.82%. It can be seen from the table that by combining the online learning ability evaluation and learning recursive ability evaluation, the model in this article can more comprehensively evaluate the online learning cognitive ability of college students. This evaluation method not only considers the strengths and weaknesses of students in different knowledge areas, but also pays attention to the growth trend of students in the learning process. On sample set i and sample set 2, the *AUC* value of the model in this article is higher than that of the other two models (traditional dynamic key-value memory network and the model with only learning ability layer). This shows that the prediction performance of the model in this article is the best on these two sample sets, which proves the effectiveness of introducing the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network. When dealing with these sample sets, the model in this article not only pays attention to the individual differences in students' ability to understand and accept knowledge, but also pays attention to the recursive features of knowledge accumulation and experience growth in the learning process. This makes the model in this article have better predictive performance and generalization ability in evaluating the cognitive ability of college students' online learning.

Table 1. Improvement effect of different improvement strategies on the model *AUC* %

Algorithm Model	Sample Set 1		Sample Set 2	
	Average Value	Highest Value	Average Value	Highest Value
Traditional dynamic key-value memory network	82.38	82.51	74.49	74.70
With only the learning ability layer	82.50	82.57	74.65	74.75
The model	82.65	82.76	74.68	74.82

Table 2. Improvement effect of different improvement strategies on the model *ACC* %

Algorithm Model	Sample Set 1		Sample Set 2	
	Average Value	Highest Value	Average Value	Highest Value
Traditional dynamic key-value memory network	77.44	77.54	75.68	75.98
With only the learning ability layer	77.54	77.56	75.79	75.84
This model	77.65	77.74	76.10	76.12

Table 2 shows the *ACC* value of the improvement effect of different improvement strategies on the model. It can be seen from the table that in the experiment of sample set 1, the average *ACC* value of the traditional dynamic key-value memory network is 77.44%, and the highest value is 77.54%; the average *ACC* value of model with only the learning ability layer is 77.54%, and the highest value is 77.56%; the average *ACC* value of this model is 77.65%, and the highest value is 77.74%. In the experiment of sample set 2, the average *ACC* value of the traditional dynamic key-value memory network is 75.68%, and the highest value is 75.98%; the average *ACC* value of the model with only the learning ability layer is 75.79%, and the highest value is 75.84%; the average *ACC* value of this model is 76.10% and the highest value is 76.12%. It can be seen from the table that the model in this article combines online learning ability evaluation and learning recursive ability evaluation, and introduces learning ability layer and learning recursive ability layer in the dynamic key-value memory network, which can more comprehensively evaluate the online learning cognitive ability of college students. This evaluation method not only pays attention to the strengths and weaknesses of students in different knowledge areas, but also pays attention to the growth trend of students in the learning process. From the perspective of *ACC* indicators, the performance of the model in this article is better than that of the other two models (traditional dynamic key-value memory network and model with only learning ability layer) on the two sample sets. This shows that the model in this article has better predictive performance on these two sample sets, and proves the effectiveness of introducing the learning ability layer and the learning recursive ability layer. The model in this article not only pays attention to individual differences in students' ability to understand and accept knowledge, but also pays attention to the recursive features of knowledge accumulation and experience growth in the learning process. This makes the model in this article have better predictive performance and generalization ability in evaluating the cognitive ability of college students' online learning.

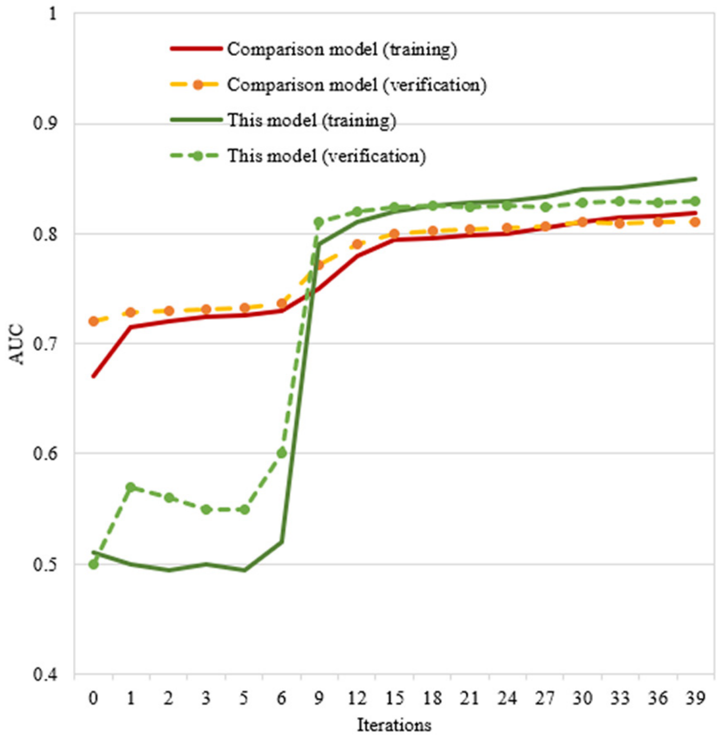

Fig. 4. *AUC* change process of training set and verification set

From the *AUC* change process of the training set and verification set model given in Figure 4 that the *AUC* value of the comparison model (traditional dynamic key-value memory network) on the training set gradually increases from 67% to 81.8%, showing better training effect. On the validation set, the *AUC* value increases from 72% to 81%, which is a relatively small increase, but the overall performance is stable. In the model of this article, on the training set, the *AUC* value increases from 51% to 85%, which is a large increase, indicating that the model has learned more effective information during the training process. On the verification set, the *AUC* value increases from 50% to 83%, a significant increase, and the final *AUC* value is higher than that of the comparison model, indicating that the model in this article performs better in terms of generalization ability. Through comparative analysis, it can be found that the *AUC* change process of this model on the training set and the verification set has high stability and generalization ability. Compared with the traditional dynamic key-value memory network, the model in this article has learned more effective information during the training process, making it more accurate and stable in evaluating students' cognitive ability in online learning. This is due to the introduction of the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network, so that the model can better capture the individual differences of students and the recursive features in the learning process.

Figure 5 shows the relationship between the completion rate of course learning tasks and the number of online learning items. Under different circumstances, the evolution of students' cognitive level may show the following features. When the number of online learning items is small and students only participate in a small number of online learning items, they can concentrate on these items, so as to better understand and master relevant knowledge. This helps to improve the cognitive level of the students, so that they can achieve better results in specific areas. When the number of online learning items is moderate and students participate in the right amount of online learning items, they need to allocate their time and energy reasonably among the various items. In this case, students may achieve better results in some areas, while maintaining a certain level of knowledge in other areas. A moderate number of items can help students broaden their knowledge and improve their interdisciplinary comprehensive quality. When the number of online learning items is high and students are involved in a large number of online learning items, it is difficult for them to devote enough time and energy to all the items. This can lead to students performing poorly on individual items, thereby lowering overall cognitive levels. In addition, too many online learning items may cause students' learning fatigue and further affect the improvement of their cognitive level.

To sum up, the rational arrangement of the number of online learning items is of great significance to the evolution of students' cognitive level. An appropriate number of online learning items can help students broaden their knowledge and improve their interdisciplinary comprehensive quality, while avoiding distraction and learning fatigue caused by too many items. Therefore, educators and students themselves should fully understand students' learning abilities and interests, and formulate appropriate online learning plans for them to improve students' cognitive level.

Table 3. Effects of different prediction models in different sample sets

Model	Sample Set 1		Sample Set 2	
	AUC	***F*1**	***AUC***	***F*1**
SVM	82.41	88.89	81.09	83.69
Decision tree	81.21	88.98	81.13	84.65
Random forest	83.02	89.76	81.91	86.64
Recurrent neural network	83.61	90.12	82.31	88.87
Transformer	84.91	90.31	83.59	89.71
This model	85.95	90.41	84.32	90.82

Table 3 shows the effect of different prediction models on different sample sets. As can be seen from the above table, the AUC and $F1$ indicators of each model on the two sample sets are as follows. The AUC and $F1$ indicators of *SVM,* decision tree and random forest on the two sample sets are better than decision tree, but slightly lower than recurrent neural network and *Transformer.* The AUC and $F1$ indicators of the recurrent neural network and *Transformer* on the two sample sets perform well, especially the $F1$

indicator on the sample set 2 performs well, indicating that the recurrent neural network has a strong ability to capture the sequence information of students' learning behaviors. Ability. The *AUC* and *F*1 indicators of the model in this article are the highest on the two sample sets, indicating that the model in this article has the best performance on the evaluation task of college students' online learning cognitive ability. This is due to the fact that the model in this article introduces the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network, so that the model can better capture the individual differences of students and the recursive features in the learning process.

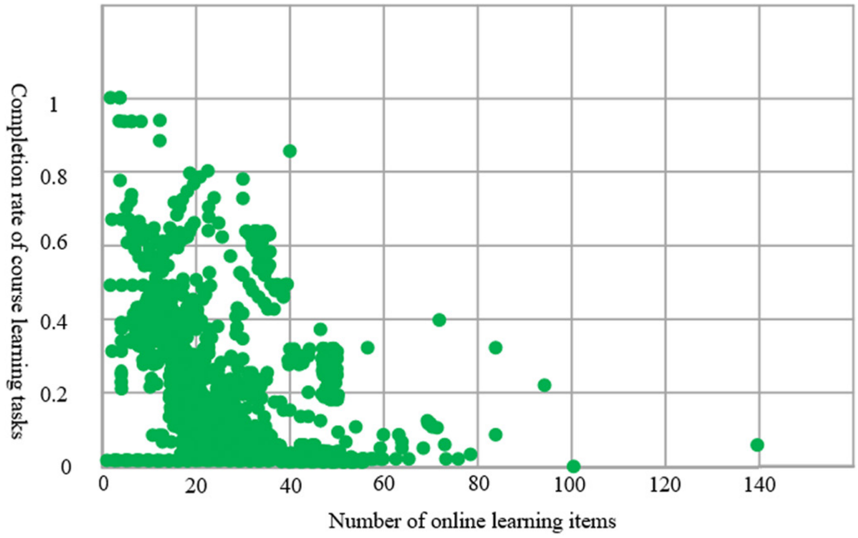

Fig. 5. Relationship between the completion rate of course learning tasks and the number of online learning items

5 Conclusions

This article studies the evaluation method of online learning cognitive ability of college students based on deep learning. The evaluation of college students' online learning cognitive ability is divided into two parts: online learning ability evaluation and learning recursive ability evaluation. By introducing the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network and constructing the corresponding evaluation model, it's better to evaluate the online learning cognitive ability of college students can be. Based on the historical learning behavior data of students in the online learning process, it's possible to predict the cognitive state of online learning, and further improve the performance of the model through data enhancement and self-attention mechanism. The experimental results show the *AUC/ACC* value of the improvement effect of different improvement strategies on the model, and the *AUC/ACC* value of the comparison test using *LSTM* and *GRU* for the learning recursive ability layer, which verifies that the model in this article has better predictive performance and generalization ability and the effectiveness of learning recursive ability layer using *LSTM* in evaluating the online learning cognitive ability of college students. In terms of ability. It shows the *AUC* change process of the training set and verification set model, discusses the relationship between the completion rate of course learning tasks and the number of online learning items, and shows the effect of different prediction models in different sample sets. It is verified that the model in this article has the best performance on the evaluation of college students' online learning cognitive ability. This is due to the fact that the model in this article introduces the learning ability layer and the learning recursive ability layer into the dynamic key-value memory network, so that the model can better capture the individual differences of students and the recursive features in the learning process.

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8 Author

Lili Zhao female, Han ethnicity, was born in 1980 in Jinzhou, Hebei Province. She won her master's degree from Nankai University. Currently, she works as lecturer in the Department of Student Affairs and Social Sciences at Shijiazhuang University of Applied Technology. Her research directions include ideological and political education, Marxism and traditional culture. In 2021, she received the honorary title of general public Learning Star in Hebei Province. In the same year, she won the first prize of excellent teaching materials and courseware of Political Theory Course, awarded by Hebei Education Department. Her Political Theory Course multimedia courseware won the first prize of outstanding achievement awarded by Shijiazhuang Municipal Education Bureau. In 2022, She also won the first prize of the Five-Minute Classroom of Party History Learning with the video titled "Know the history, Love the Party; Know the history, Love the country", awarded by Shijiazhuang Education Bureau. Email: 2005110229@sjzpt.edu.cn. Orcid: https://orcid.org/0000-0002-3775-1858.

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