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PAPER

Cognitive Status Analysis for Recognizing and Managing Students' Learning Behaviors

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ABSTRACT

Online learning environments have become increasingly popular due to their flexibility and convenience, but they also present new challenges, such as maintaining student motivation and engagement. To address these challenges, it is crucial to understand and predict students' learning behaviors. This study explores the recognition and management of students' learning behaviors through cognitive status analysis. By conducting a thorough analysis of students' cognitive status and applying advanced deep learning models and algorithms, this study demonstrates the effectiveness of recognizing and managing students' learning behaviors. The proposed model combines convolutional neural networks and long short-term memory networks with attention mechanisms, which incorporate cognitive status evaluation features and use them as filters for text information. The model's focus on text sentences with distinctive features in cognitive status evaluation leads to more effective recognition and management of students' learning behaviors. Additionally, by integrating Most Informative Propositions and Semantic Propositional Value into the deep learning model, this study achieved excellent results in cognitive status evaluation recognition tasks. Further experiments show that by mixing different features and using advanced algorithms, the final model achieves high classification accuracy and $F1$ scores on multiple types of learning behaviors. Continuous assessment of students' cognitive status and learning behaviors can lead to the development of effective learning strategies and intervention measures, which can enhance students' mastery of knowledge and overall performance.

KEYWORDS

cognitive status analysis, learning behavior recognition, learning behavior management

1 INTRODUCTION

In the field of education in the 21st century, the rapid development of network technology has made online learning a prevalent form of education. The convenience and flexibility of online learning provide students with more learning opportunities, particularly in special circumstances such as the COVID-19 pandemic, where it has

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played a crucial role [1–5]. However, compared to traditional face-to-face learning, the characteristics of online learning environments make the analysis and management of students' learning behaviors and cognitive conditions more complex [6–8]. Effectively managing and optimizing these online learning processes to improve students' learning efficiency and performance has become a significant challenge in the field of education. Therefore, the effective identification and management of students' learning behaviors and understanding their cognitive conditions are of significant importance for enhancing the educational effectiveness of online learning.

Students' cognitive conditions, including their knowledge mastery, problem-solving abilities, and learning strategies, are key factors that influence their academic performance and learning behaviors [9–12]. In the online learning environment, analyzing students' cognitive conditions can provide a more accurate assessment of their learning progress and needs, enabling the provision of personalized learning resources and support [13, 14]. This is valuable for promoting students' learning motivation, improving learning efficiency, and cultivating lifelong learning skills [15–17]. Furthermore, predicting students' learning behaviors based on their cognitive conditions can help educators with the timely identification of potential learning difficulties and take appropriate intervention measures, thus improving students' academic performance and satisfaction.

However, existing methods for identifying students' learning behaviors and analyzing cognitive conditions have some notable limitations when applied to online learning environments. Many methods heavily rely on direct feedback from students or simple behavioral data such as exam scores and completion speed, which often fail to comprehensively reflect students' true cognitive states. Additionally, some methods struggle to effectively capture and analyze semantic information, word collocations, and contextual information relevant to cognitive conditions when processing textual information. These limitations restrict the accuracy and effectiveness of these methods in assessing and predicting students' learning behaviors.

In light of this, this article takes the teaching of Chinese as a foreign language as an example, and conducts research on the identification and management of students' learning behaviors based on the analysis of their cognitive states. It proposes a cognitive state analysis method for online learning and a student learning behavior prediction algorithm based on the assessment of cognitive states. Our method focuses on evaluating students' performance on various knowledge points and questions in middle school, conducting in-depth analysis of their cognitive conditions. Using an attention mechanism model, we emphasize textual information relevant to cognitive condition evaluation. This model effectively captures and analyzes differences in semantics, word collocations, and contextual information, enabling our method to demonstrate good practical application in identifying and predicting students' learning behaviors.

2 METHODS FOR ANALYZING COGNITIVE STATES IN ONLINE LEARNING

Analyzing students' cognitive states is crucial in the context of identifying and managing learning behaviors. By analyzing students' cognitive states, educators can better understand students' learning needs and preferences, which can help provide more personalized learning resources and teaching strategies, thereby improving learning efficiency. Analyzing students' cognitive states can also help teachers identify students' weak areas in a particular knowledge or skill, in order to provide necessary tutoring and support and prevent students from feeling frustrated during the learning process. Furthermore, cognitive state analysis can help students gain a clearer understanding of their learning progress and status, which not only enhances their confidence but also motivates them to engage in independent learning.

Online learning differs from traditional teaching methods, as students often need to learn in a more self-directed and flexible environment. This requires an evaluation method that can adapt to the characteristics of online learning, including the lack of time and location restrictions, rich interaction, and diverse learning resources. Traditional methods such as total score and weighted average are too simplistic and cannot comprehensively reflect students' cognitive states in online learning. However, knowledge point evaluation models and exercise evaluation models designed specifically for online learning can more accurately capture and analyze students' learning behaviors.

2.1 Knowledge point evaluation

This paper constructs a knowledge point evaluation model for online learning platforms. By tracking and tallying the number of correct and incorrect choices made by students for each knowledge point during the exercise process, this model can dynamically evaluate students' mastery of each knowledge point. This dynamic evaluation is more accurate than a one-time exam or test and allows for a more detailed understanding of students' understanding and application abilities of each knowledge point, as each exercise question may involve multiple knowledge points. This is of great value in identifying students' weaknesses and devising targeted learning plans.

The following parameters related to evaluating knowledge points based on students' exercise behaviors during online learning are defined. Suppose the number of times a knowledge point is correctly chosen in a question by a student after completing the exercise is represented by *NOCR*, and the number of times it is incorrectly chosen is represented by *NOCW*. The historical total of correct and incorrect choices for a knowledge point before the student starts the exercise is represented by *NOPR* and *NOPW*, respectively. Based on these definitions, the following parameters can be obtained.

The sum of total correct choices, *TOR*, can be calculated as follows:

$$TOR = NOCR + NOPR \tag{1}$$

The sum of total incorrect choices, *TOW*, can be calculated as follows:

$$TOW = NOCW + NOPW \tag{2}$$

The current correct rate, *CRR*, can be calculated as follows:

$$CRR = \frac{COR}{COR + COW} \tag{3}$$

The total correct rate, *TRR*, can be calculated as follows:

$$TRR = \frac{TOR}{TOR + TOW} \tag{4}$$

The knowledge point score, DF_j, can be calculated as follows:

$$DF_j = TRR \times 100 \tag{5}$$

2.2 Exercise evaluation

This paper further constructs an exercise evaluation model for online learning platforms. By dividing knowledge points into "understanding, comprehension, mastery, and application" categories and assigning different weights, this model can more precisely characterize students' performance at different cognitive levels. This categorization and weight assignment can more accurately reflect students' mastery of various cognitive skills required in exercises. As different knowledge points have different levels of difficulty and importance, this model assigns different weights to different knowledge points to reflect the complexity and importance of each knowledge point in the exercise, thus more accurately evaluating students' performance. Moreover, as this model combines the characteristics of cognitive learning models and traditional weighted average methods, it can comprehensively analyze exercises, including students' mastery of each knowledge point in the exercise, which helps to gain a deeper understanding of students' learning behaviors and performance factors. Figure 1 shows a schematic diagram of the exercise model.

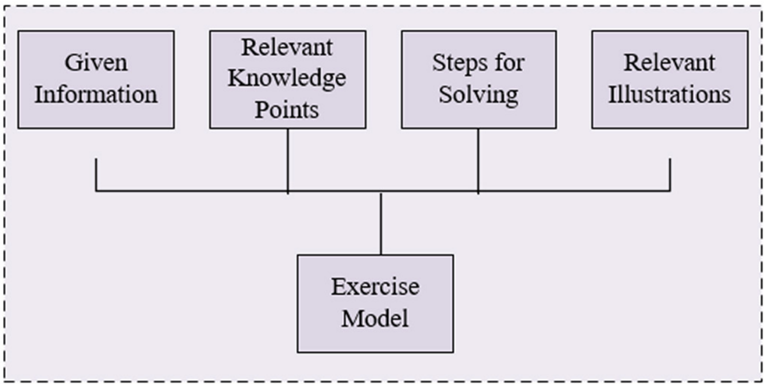

Fig. 1. Schematic diagram of the exercise model

This paper sets the weight of knowledge points, Q_u, to four levels: 1, 2, 3, and 4, i.e., $Q_u = U(U=1,2,3,4)$, with the value of U indicating the strength of the importance of the exercise. Suppose the exercise involves b knowledge points, and the sum of all knowledge point weights is represented by $\sum_{u=1}^{b} Q_u$. Let the correct rate of the selection times for knowledge point u in the current question be represented by CRR_u. The score obtained after completing the current question is represented by DF_o. The score of the exercise is calculated based on the following formula, which multiplies CRR_u by the corresponding knowledge point weight and divides it by the total weight, then records it in the database:

$$DF_o = \frac{\sum_{u=1}^{b} \left(Q_u \times CRR_u\right)}{\sum_{u=1}^{b} Q_u} \times 100 \tag{6}$$

3 A STUDENT LEARNING BEHAVIOR PREDICTION ALGORITHM BASED ON COGNITIVE STATE EVALUATION

The algorithm for predicting students' learning behaviors based on cognitive condition evaluation is proposed in this section. Traditional word frequency feature design primarily focuses on the frequency of word occurrences in the text but lacks the capture of deep semantic content. In the context of identifying and managing students' learning behaviors based on cognitive condition analysis, this study adopts the aforementioned cognitive condition evaluation attention mechanism to predict students' learning behaviors. The introduced cognitive condition evaluation attention mechanism can focus on the deep semantics of the text, including word collocations and contextual information, thereby enabling a more in-depth and accurate assessment of students' cognitive conditions. Furthermore, this mechanism can flexibly capture subtle differences in students' behaviors when using online learning platforms, providing richer information for analyzing students' learning behaviors. Figure 2 illustrates the process of predicting students' learning behaviors.

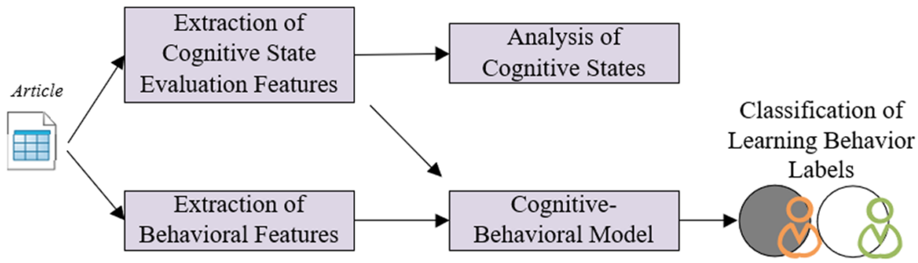

Fig. 2. Process of predicting students' learning behaviors

The combination of Convolutional Neural Networks (CNN) and Recurrent Neural Networks (RNN) is employed in this study to extract rich features, including syntactic and semantic information, from the text. CNN is effective in capturing local features such as phrases and word combinations, while RNN is capable of capturing dependencies in time or sequences, such as sentence order. By integrating CNN, RNN, and the cognitive condition evaluation attention module, the model can comprehensively process various types of information, including local features, sequential relationships, and key information related to cognitive conditions in the text. This enables the model to dynamically learn and understand students' behaviors and changes in cognitive states during the learning process, with a focus on text information highly relevant to students' cognitive conditions.

3.1 Convolutional recurrent neural network

To capture the semantic information of the cognitive condition evaluation text, a convolutional and recurrent neural network module is constructed in the model. Taking a single cognitive condition evaluation text sample $SA = (TE, LA)$ as an example, the words $\{z_1,z_2,\ldots,z_l\}$ in the text sentence are represented using *Glove* word embeddings. Assuming the number of words in the sentence is denoted by l, the input matrix size for each sentence is l*300. The content of the matrix from $z_{u:u+g-1}$ is scanned by a convolutional kernel j with a window size of g to obtain the corresponding feature value. Assuming the content from the u-th row to the $u+g-1$-th row in the input matrix is represented by $z_{u:u+g-1}$, the weight matrix is represented by q_j, the bias of the convolutional operation is represented by n, and the activation function is represented by d, the following equations describe the convolutional operation:

$$v_{ju} = d(q_j \cdot z_{u:u+g-1} + n_j) \tag{7}$$

$$v_j = AV\_PO([v_{j1}, v_{j2}, \ldots, v_{j(l-g+1)}]) \tag{8}$$

$$v_k = [v_1, v_2, \ldots, v_j] \tag{9}$$

The resulting feature map obtained after sequence scanning can be represented as $[v_{j1}, v_{j2}, \ldots, v_{j(l-g+1)}]$. After obtaining the spatial local information features at the sentence level in the cognitive condition evaluation text through the above steps, further encoding of the serialized text sentence information is required. In this study, a bidirectional Long Short-Term Memory (*LSTM*) network is introduced to achieve this information processing. Assuming the weights of the corresponding gates are represented by Q, the biases are represented by n, and the cell state for recording sequence status information and generating g_k is represented by V_k. The following equations describe the calculations:

$$FO_k = \delta(Q_{FO} \cdot [g_{k-1}, v_k] + n_{FO}) \tag{10}$$

$$IN_k = \delta(Q_{IN} \cdot [g_{k-1}, v_k] + n_{IN}) \tag{11}$$

$$\tilde{V}_K = \tanh(Q_V \cdot [g_{k-1}, v_k] + n_V) \tag{12}$$

$$V_k = FO_k * V_{k-1} + IN_k * \tilde{V}_K \tag{13}$$

$$OU_k = \delta(Q_{OU} \cdot [g_{k-1}, v_k] + n_{OU}) \tag{14}$$

$$g_k = \tanh(V_k) * OU_k \tag{15}$$

The bidirectional LSTM network consists of input gates, output gates, and forget gates. Assuming the sentence representation of the *k*-th cognitive condition evaluation text obtained after convolutional operations is represented by v_k, and the output of the *k*-th position obtained from the bidirectional LSTM network is represented by g_k, each gate is computed based on the current position's input $[g_{k-1}, v_k]$. The newly generated g_k and V_k will be used in the calculation of the next position's $g + m$ hidden layer.

To capture the influence of subsequent text on previous text in the cognitive condition evaluation text, a bidirectional LSTM network is used in this study. In this network model, the contextual representation sequence of the overall text is represented by $\{g_1, g_1, \ldots, g_b\}$, where b denotes the number of sentences in the text, and the sentence representation output contains outputs from both directions. The equations below describe the representations:

$$\vec{g}_K = HI\_LA(v_k, g_{k-1}) \tag{16}$$

$$\overleftarrow{g}_K = HI\_LA(v_k, g_{k+1}) \tag{17}$$

$$g_k = [\vec{g}_K, \overleftarrow{g}_K] \tag{18}$$

3.2 Attention-based cognitive state evaluation

Cognitive condition evaluation attention is employed to distinguish between the literal semantic meaning of the target word in the cognitive condition evaluation text and the contextual semantic meaning in the surrounding context. The MIP and SPV from the cognitive condition evaluation identification theory are fused within the framework of deep learning models. This fusion utilizes the advantages of deep learning in processing large-scale data and extracting complex features, while incorporating domain knowledge to enhance the accuracy and reliability of the model.

To distinguish between the literal semantic meaning of the target word and the contextual semantic meaning in the cognitive condition evaluation text, an MIP model is introduced. Assuming the *softmax* activation function is denoted by δ, the *GIoVe* word vector for the word at that position is denoted by h_y, the ELMO vector is denoted by r_y, and the hidden state representation of the bidirectional LSTM network at that position is denoted by g_y. The trainable network parameters are denoted by q, the bias is denoted by n, and the concatenation of vectors is denoted by [;]. The following equations present the probability prediction for the cognitive condition evaluation of the word at position y:

$$o(\hat{t}_y \mid g_y, h_y) = \delta(q^{\top}[g_y, h_y] + n) \tag{19}$$

$$g_y = d_{JYWL}([g_y, h_y], \overrightarrow{g}_{y-1}, \overleftarrow{g}_{y-1}) \tag{20}$$

To detect the semantic conflict between the target word in the cognitive condition evaluation text and the context in which it is situated, an *SPV* model is employed to determine its cognitive condition evaluation category. The following equation presents the final probability prediction function for the cognitive condition evaluation:

$$o(\hat{t}_y \mid g_y, v_y^b) = \delta(q^{\top}[g_y, v_y^b] + n) \tag{21}$$

From the equation above, it can be observed that the learning behavior label for y can be inferred based on the hidden state g_y of the target word in the cognitive condition evaluation text and the attention representation v_y^b of the context.

By incorporating cognitive condition evaluation information into the text feature vector, the model can access more information, which helps enhance the richness and diversity of the features, enabling the model to better understand and capture students' learning behaviors accurately. This focus capability allows the model to prioritize and consider information that is important in cognitive evaluation, thereby improving the efficiency and accuracy of the analysis.

The prediction of students' learning behaviors based on cognitive condition evaluation involves a multi-stage process. Figure 3 illustrates the framework of the algorithm for predicting students' learning behaviors based on cognitive condition evaluation. The following outlines the prediction approach and steps:

(1) Data collection: First, collect students' learning data from online learning platforms, including but not limited to answer records, learning time, interaction data, feedback, and evaluations.

(2) Text processing and feature extraction: Preprocess the collected text data, including tokenization and stop word removal. Then, extract word-level features for cognitive condition evaluation using the word sequence labeling approach and generate cognitive condition evaluation vectors.

(3) Construct cognitive condition evaluation model: Generate the contextual representation of sentences. Combine the cognitive condition evaluation attention module to extract and aggregate text information, with a focus on text sentences that have specific characteristics in cognitive condition evaluation usage.

(4) Label students' learning behaviors: Assign labels to students' learning behaviors based on their learning data and actions, such as "active participation", "in need of assistance", "excellent performance", etc.

(5) Build learning behavior prediction model: Use the cognitive condition evaluation results as input features and the students' learning behavior labels as the target variable.

(6) Model training and validation: Train the learning behavior prediction model using historical data and evaluate its performance using cross-validation or a separate validation dataset.

(7) Model optimization: Adjust and optimize model parameters based on the validation results to improve the accuracy of the predictions.

(8) Real-time prediction and intervention: Deploy the optimized model to online learning platforms, monitor students' learning data in real time, predict their learning behaviors based on the cognitive condition evaluation identification results, and take appropriate teaching interventions based on the predicted results.

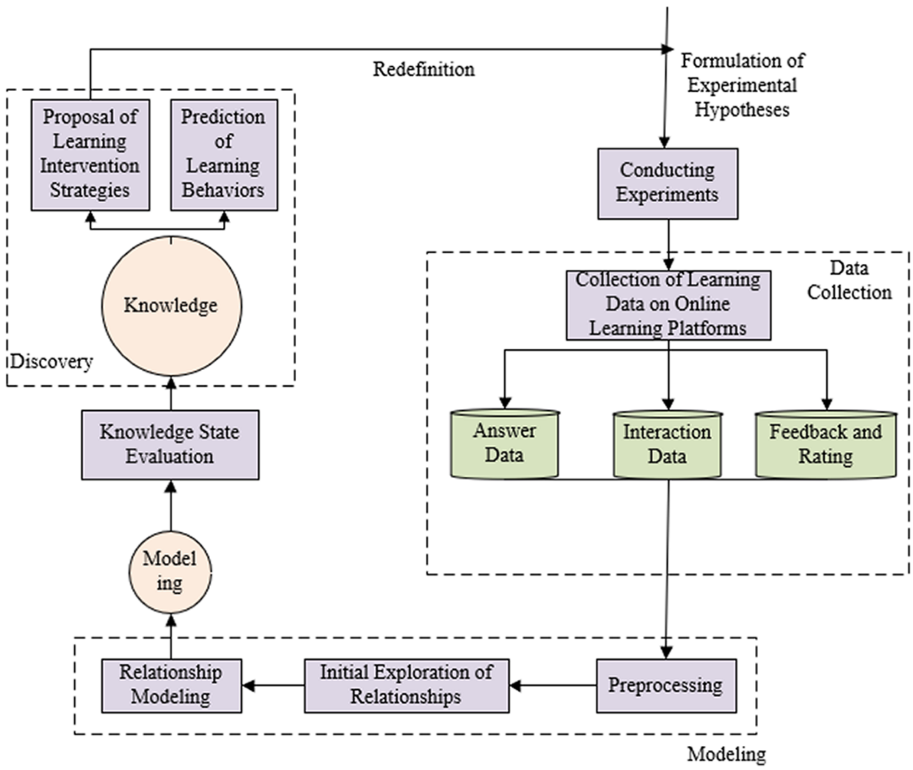

Fig. 3. Framework of the algorithm for predicting students' learning behaviors

4 RESULT AND DISCUSSION

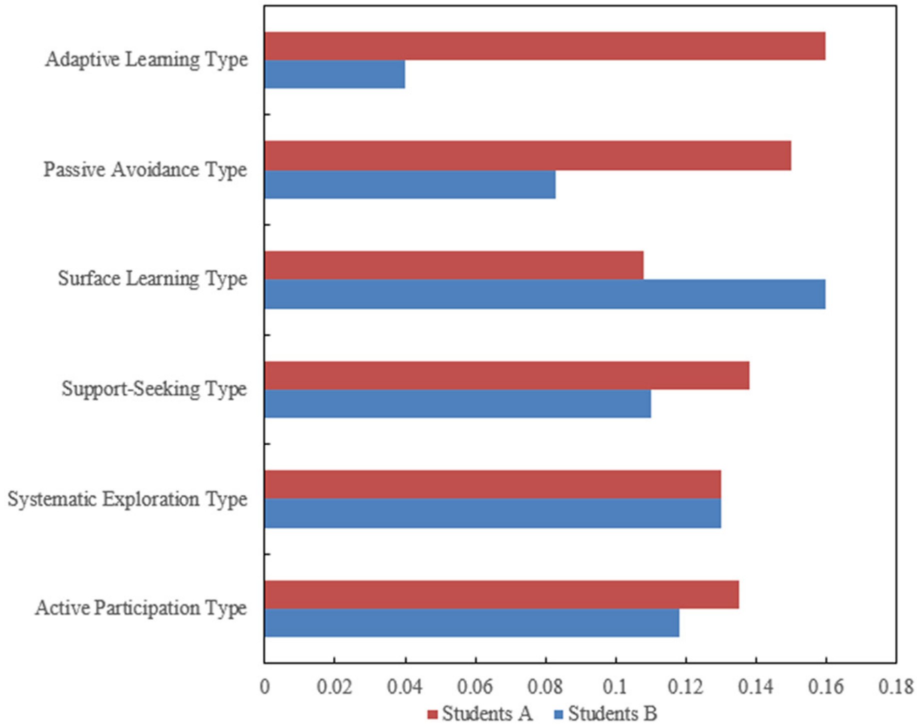

Fig. 4. Analysis of students' cognitive state scores under different learning behavior types

Figure 4 presents the scores of students' cognitive states under different learning behavior types. These scores are normalized and represent the relative levels of students' performance in these behavior types. In the active participation learning behavior, Student A obtained a score of 0.135, while Student B obtained a score of 0.118. This indicates that Student A slightly outperformed Student B by actively participating in learning activities and being more willing to engage and invest in the learning process. In the systematic exploration learning behavior, both Student A and Student B obtained a score of 0.13. This suggests that both students have a similar inclination towards exploring and attempting to understand the complexity of the learning materials. In the need-for-support learning behavior, Student A obtained a score of 0.138, while Student B obtained a score of 0.11. This indicates that Student A relies more on external support, such as teacher or peer assistance, to complete learning tasks. In the surface learning behavior, Student B obtained a score of 0.16, while Student A obtained a score of 0.108. This indicates that Student B tends to engage in surface-level learning, which means they do not deeply understand the materials but focus more on memorization and test-taking skills. In the passive avoidance learning behavior, Student A obtained a score of 0.15, while Student B obtained a score of 0.083. This suggests that Student A tends to exhibit more passive behaviors in the learning process, such as avoiding participation or procrastinating. In the adaptive learning behavior, Student A obtained a score of 0.16, while Student B obtained a score of 0.04. This indicates that Student A is more successful in adapting and adjusting learning strategies to cope with different learning environments and challenges.

From the above analysis, it can be observed that different students obtained different scores in cognitive states under different learning behavior types. This understanding of the association between learning behavior types and cognitive state scores can help educators comprehend students' learning preferences and potential challenges, and accordingly adjust teaching methods and provide support.

Table 1. F1 Scores of different classifiers for learning behavior classification

Classifier	Active Participation Type	Systematic Exploration Type	Support-Seeking Type	Surface Learning Type	Passive Avoidance Type	Adaptive Learning Type
LR	0.52	0.61	0.55	0.62	0.58	0.54
SVM	0.68	0.63	0.51	0.69	0.51	0.61
MI+SPV	0.69	0.68	0.63	0.74	0.56	0.68

The Table 1 shows the $F1$ scores of three classifiers (*LR*, *SVM*, *MI+SPV*) for six different learning behavior types classification. In the active participation learning behavior, *MI+SPV* achieved the highest $F1$ score of 0.69, surpassing the other classifiers, indicating that *MI+SPV* has the best precision and recall in identifying active participation behavior. In the systematic exploration learning behavior, *MI+SPV* also outperformed the other classifiers with an $F1$ score of 0.68, demonstrating its excellent performance in identifying systematic exploration behavior. In the need-for-support learning behavior, *MI+SPV* achieved an $F1$ score of 0.63, higher than the other classifiers, indicating good precision and recall in identifying the need-for-support behavior. In the surface learning behavior, *MI+SPV* obtained the highest $F1$ score of 0.74, displaying the best precision and recall in identifying surface learning behavior. In the passive avoidance learning behavior, *LR* classifier had the highest $F1$ score of 0.58, slightly ahead of the other classifiers, although *MI+SPV*'s performance was also close. In the adaptive learning behavior, *MI+SPV* achieved the highest $F1$ score of 0.68, demonstrating its superior precision and recall in identifying adaptive learning behavior. Overall, *MI+SPV* classifier obtained the highest $F1$ scores in five out of the six categories, indicating its best performance in recognizing these learning behaviors.

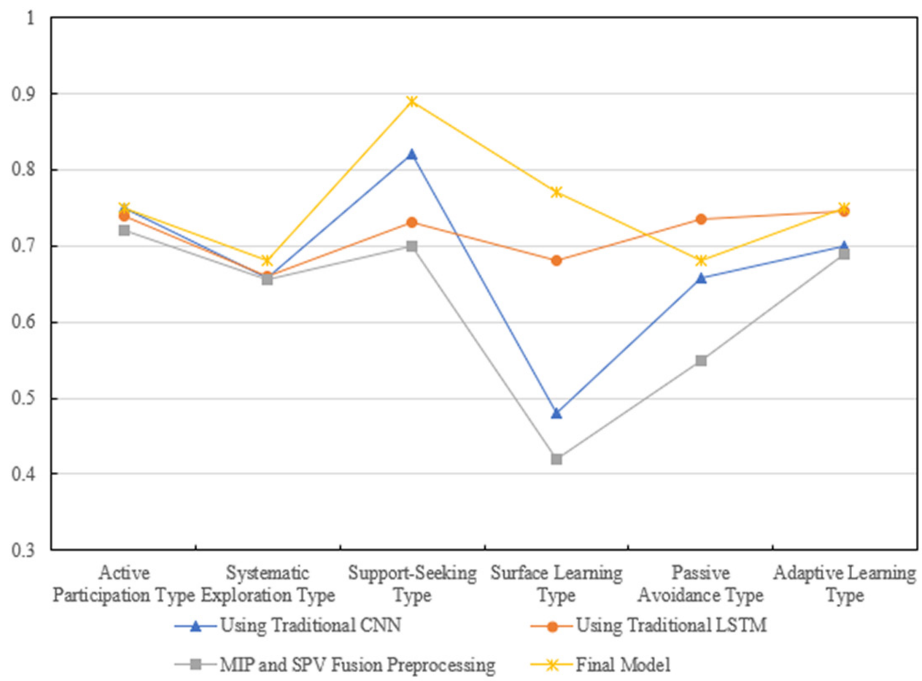

Fig. 5. Accuracy of different algorithms for classifying different learning behavior types

Figure 5 illustrates the accuracy of four different algorithms for classifying six different learning behavior types. It can be observed that in the active participation learning behavior, both the traditional *CNN* and the final model achieved the same accuracy of 0.75, which is the highest among the four algorithms. This indicates that these two models are more effective in recognizing active participation behavior. In the systematic exploration learning behavior, the final model has a slightly higher accuracy of 0.68 in this category compared to the other three algorithms, suggesting a certain advantage in recognizing systematic exploration behavior. In the need-for-support learning behavior, the final model significantly outperformed the other algorithms with an accuracy of 0.89 in this category, indicating its effectiveness in identifying the need-for-support behavior far exceeds the other algorithms. In the surface learning behavior, the final model achieved an accuracy of 0.77, significantly higher than the other algorithms, demonstrating its precision in recognizing surface learning behavior. In the passive avoidance learning behavior, the accuracy of using the traditional *LSTM* was 0.735, which is the highest among the four algorithms. This suggests that the traditional *LSTM* performs better in recognizing passive avoidance behavior. In the adaptive learning behavior, both the traditional *LSTM* and the final model achieved the same accuracy of 0.75, indicating their effectiveness in recognizing adaptive learning behavior. Based on the above analysis, it can be concluded that the final model exhibits the best performance in classifying the six different learning behavior types from different perspectives, indicating its superior ability to recognize these learning behaviors.

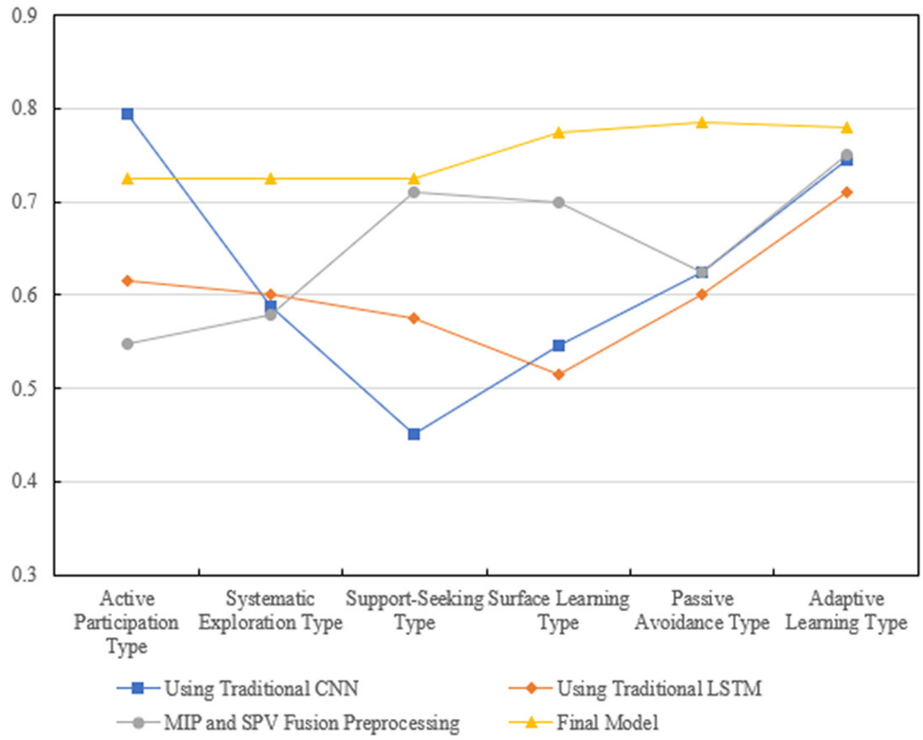

Fig. 6. F1 Scores of different algorithms for classifying different learning behavior types

Figure 6 displays the $F1$ scores of four different algorithms for classifying six different learning behavior types. In the active participation learning behavior, the traditional *CNN* achieved the highest $F1$ score of 0.795 among the four algorithms.

This indicates that the traditional *CNN* has good precision and recall in recognizing active participation behavior. In the systematic exploration learning behavior, the final model achieved the highest $F1$ score of 0.725 in this category, surpassing the other three algorithms, demonstrating its excellent performance in recognizing systematic exploration behavior. In the need-for-support behavior, the final model obtained an $F1$ score of 0.725, higher than the other algorithms, indicating good precision and recall in identifying the need-for-support behavior. In the surface learning behavior, the final model obtained the highest $F1$ score of 0.775, surpassing the other algorithms, indicating its best performance in recognizing surface learning behavior. In the passive avoidance learning behavior, the final model achieved the highest $F1$ score of 0.785, surpassing the other algorithms. In the adaptive learning behavior, the final model proposed in this paper obtained an $F1$ score of 0.78, the highest among the four algorithms, indicating its good performance in recognizing adaptive learning behavior. In conclusion, the final model exhibits the best performance in classifying the six different learning behavior types from different perspectives, demonstrating its effectiveness in recognizing these learning behaviors.

The Table 2 presents the mean and standard deviation (*SD*) of cognitive state performance in knowledge point evaluation, exercise evaluation, and comprehensive evaluation at different time points (before training, immediately after training, two weeks later, four weeks later). For knowledge point evaluation, there was a significant improvement in the mean score from before training to immediately after training, indicating the positive effect of training on knowledge acquisition. However, at the two-week and four-week time points, the mean scores began to decline gradually, suggesting a weakening of the mastery of knowledge points over time. In terms of exercise evaluation, the mean score showed a slight increase immediately after training, but remained relatively stable at the two-week and four-week time points. This implies that training had some positive impact on exercise-solving ability, but the long-term effect was not significant. For comprehensive evaluation, a significant improvement in the mean score was observed immediately after training. However, similar to knowledge point evaluation, the mean scores started to decline gradually at the two-week and four-week time points, indicating a long-term decline in knowledge and skill retention. In summary, training has a positive impact on students' knowledge point mastery and exercise-solving ability, particularly immediately after training. However, without continuous learning or review, these effects gradually weaken. This highlights the importance of continuous learning and review in education and learning management.

Table 2. Cognitive state performance in multiple learning behavior management tests

	Before Training		Immediate After Training		Two Weeks Later		Four Weeks Later	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Knowledge Point Evaluation	0.2518	0.1629	0.4152	0.1528	0.3925	0.1057	0.3417	0.1692
Exercise Evaluation	0.3629	0.1857	0.4362	0.1427	0.3847	0.1635	0.3925	0.1384
Comprehensive Evaluation	0.1547	0.1052	0.3958	0.1639	0.3625	0.1858	0.3041	0.1527

Table 3. Independent sample t-test results between multiple learning behavior management post-tests and pre-training

	Immediate After Training		Two Weeks Later		Four Weeks Later	
	t	*p*	*t*	*p*	*t*	*p*
Knowledge Point Evaluation	–4.251	0.015***	–4.635	0.024***	–4.158	0.041**
Exercise Evaluation	–3.625	0.035***	–1.528	0.061**	–0.925	0.362
Comprehensive Evaluation	–3.961	0.062***	–6.925	0.036***	–6.417	0.014***

The Table 3 presents the independent sample *T*-test results between multiple learning behavior management post-tests and pre-training at different time points (immediate after training, two weeks later, four weeks later). This test is commonly used to determine if there are significant differences between two independent samples. Here, we can see the *T*-values and *P*-values for knowledge point evaluation, exercise evaluation, and comprehensive evaluation at the three time points. Regarding knowledge point evaluation, the *P*-values indicate significant differences ($p<0.05$) at all three time points. This suggests that training has a significant effect on knowledge point mastery. The *T*-values for knowledge point evaluation are negative at all time points, indicating that the pre-training scores were lower than the post-training scores. For exercise evaluation, the *P*-value indicates a significant difference ($p<0.05$) immediately after training, but the *P*-values increase at the two-week and four-week time points, especially at the four-week point where the *P*-value exceeds 0.05, suggesting that the difference is no longer significant. The *T*-value for exercise evaluation is negative immediately after training, indicating a positive effect of training on exercise-solving ability, but this effect diminishes over time. In terms of comprehensive evaluation, significant *P*-values ($p<0.05$) are observed at all three time points, indicating a significant effect of training on comprehensive evaluation. The T-values are negative at all time points, indicating that the pre-training scores were lower than the post-training scores. These results suggest that training has sustained positive effects on knowledge point evaluation and comprehensive evaluation, while the impact on exercise evaluation diminishes over time. Knowledge point evaluation and comprehensive evaluation demonstrate significant improvements at all time points immediately after training, whereas the improvement in exercise evaluation is mainly observed immediately after training. These findings provide insights for educators and learning management personnel to develop effective teaching and learning strategies.

5 CONCLUSION

In online learning environments, the evaluation of students' cognitive states is an important factor in understanding and predicting their learning behaviors. By assessing students' cognitive states, educators and platforms can better understand students' learning needs and behaviors. It is crucial to employ appropriate models and algorithms to analyze students' cognitive states and learning behaviors. In this paper, deep learning models and attention mechanisms were applied in this context. By integrating attention mechanisms into the models, the focus on text information relevant to cognitive state evaluation can be enhanced, thereby improving the model's performance. This paper fully acknowledges the correlation between cognitive state evaluation and learning behaviors. Students' cognitive states are closely related to their learning behaviors. For example, students who actively participate may achieve higher scores in cognitive assessment, while students who passively avoid may score lower. By analyzing these relationships, more accurate predictions of students' learning behaviors can be made. When comparing different models and algorithms, differences in classification accuracy and F-scores were observed. Some models performed excellently in certain types of learning behaviors but less so in other types. By combining different features and using methods such as MIP and SPV, the final model typically achieved high performance across multiple learning behavior types.

6 ACKNOWLEDGMENT

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