Online-Journals.org

iJET International Journal of Emerging Technologies in Learning

iJET | eISSN: 1863-0383 | Vol. 18 No. 20 (2023) | OPEN ACCESS

https://doi.org/10.3991/ijet.v18i20.44217

PAPER

Smart Teaching Systems: A Hybrid Framework of Reinforced Learning and Deep Learning

Yijiao Sun[1], Wei Huang[1](✉), Zhiwen Wang[2], Xiaofeng Xu[1], Min Wen[1], Pei Wu[1]

[1]Department of Nursing, Yueyang Vocational and Technical College, Yueyang, China

[2]Institute of Biology and Medicine, College of Life and Health Sciences, Wuhan University of Science and Technology, Wuhan, China

ycc161118@163.com

ABSTRACT

As vocational education is transforming constantly, there is an urgent demand in the field of education for smart teaching systems to be able to respond to students' personal learning needs in a more dynamic way, but a review of currently available algorithms reveals that the common application of existing methods lacks a deep enough understanding of students' individual differences. Out of these concerns, this study aims to propose a novel and hybrid framework for the design of smart teaching systems based on reinforced learning and deep learning, so as to overcome the shortcomings of existing research and more accurately predict students' personal needs. Besides, an end-to-end model with a retrieval attention mechanism has been designed for generating responses with precise information about students' learning needs. This study provides a smart teaching scheme for vocational education that is new, efficient, and humane, while also providing a solid theoretical foundation for the reform and innovation of the education system in the future.

KEYWORDS

smart teaching system, vocational education, reinforced learning, deep learning, hybrid framework, retrieval attention mechanism, prediction of personal needs

1 INTRODUCTION

In modern vocational education, it's becoming increasingly difficult for traditional teaching methods to meet the ever-changing educational needs [1] [2], especially in the context of Industry 4.0, it is required that vocational education keep up with the pace of the era and adapt to the needs in the training of new techniques and skills [3–5]. However, current teaching systems usually lack the flexibility or adaptability to cope with the personal needs of different students [6–8], so it is a beneficial exploration to introduce the hybrid framework of reinforced learning and deep learning into smart teaching systems [9–11]. Smart teaching that is more dynamic, personalized, and efficient could be achieved with the help of advanced artificial intelligence (AI) technology, which is conducive to promoting reform and innovation in the field

Sun, Y., Huang, W., Wang, Z., Xu, X., Wen, M., Wu, P. (2023). Smart Teaching Systems: A Hybrid Framework of Reinforced Learning and Deep Learning. *International Journal of Emerging Technologies in Learning (iJET)*, 18(20), pp. 37–50. https://doi.org/10.3991/ijet.v18i20.44217

Article submitted 2023-06-13. Revision uploaded 2023-08-13. Final acceptance 2023-08-21.

of vocational education [12–15]. This research is not only closely linked to current technological trends and educational needs, but it also has far-reaching strategic significance for the future development of the education system.

After a review of literature on smart teaching systems, it was found that there are some flaws with existing methods, such as that some systems rely only on basic algorithms, lacking a deep understanding of students' individual differences [16–18]. For some systems, there is still room for improvement in terms of the accuracy and usefulness of generated responses and feedback, and current techniques have obvious limitations in predicting student needs and giving targeted responses.

The research conducted in this paper has two parts: first, the learning needs prediction of smart teaching systems was discussed based on a hybrid framework of reinforced learning and deep learning; through the combination of the two, the personal needs of students could be better understood and predicted; and second, an end-to-end model with a retrieval attention mechanism was proposed for generating responses that contain precise information about students' needs. This new method can overcome some shortcomings of existing techniques, offering a smart teaching solution that is more efficient, flexible, and user-friendly for vocational education. The research findings of this paper can promote the application of AI in education as well as provide a solid theoretical foundation for the future reform and innovation of the education system.

2 LEARNING NEEDS PREDICTION OF SMART TEACHING SYSTEM

Learning needs prediction enables a smart teaching system to understand each student's learning goals, interests, and ability levels, thereby creating personalized teaching plans and strategies that help to improve students' learning efficiency, satisfaction, relieve frustration, and reduce churn rate. Based on an accurate prediction of students' learning needs, educational resources can be allocated to students who need them the most, increasing resource utilization efficiency while also ensuring that each student receives proper support and attention.

2.1 Model of deep learning

In this paper, a learning needs prediction model for smart teaching systems is proposed that is based on deep learning (Gated Recurrent Unit, *GRU*) and reinforced learning (*Q-learning* algorithm), aiming at giving short-term predictions on students' needs when using smart teaching systems by analyzing a series of quantifiable influencing factors. Influencing factors from eight aspects considered as *GRU* input are listed below:

1. Learning progress of students: records of courses and projects completed by students and their performance at each stage.
2. Learning style and preference: Students' learning styles and preferences are quantified based on their learning materials and activities.
3. Learning time distribution: the time period in a day that students usually use to learn.
4. Learning environment and device: information about the devices (such as desktops, laptops, or cell phones) used by students for learning and connecting speed, etc.

5. Learning interaction and pattern: frequency and type of interactions between a student and the teaching platform, classmates, and teachers.
6. Feedback and rating of students: feedback and ratings given by students on courses and textbooks, including information of satisfaction, difficulty, and other aspects.
7. Learning performance: students' performance in exams, quizzes, and projects.
8. History learning behavior and achievement: students' past learning history and achievement, which are used to capture their learning trends and patterns over time.

Based on the combinations of the above factors, *GRU* can capture the complex patterns of students' learning behaviors and needs and use the *Q-learning* algorithm to perform reinforced learning to achieve accurate short-term learning needs prediction in the smart teaching system. This integrated method combines the powerful pattern recognition ability of deep learning with the adaptive decision-making ability of reinforced learning, providing new possibilities for effective and personalized smart teaching.

Assuming, Z_y represents the input vector at time moment y; W_r, W_z, W_h, U_r, U_z, and U_h are weight matrices; n_e, n_x, and n_g are bias vectors; $\delta(\cdot)$ and $tanh(\cdot)$ are activation functions; g_{y-1} represents the output state at time moment $y-1$; e_y represents the value of reset gate, X_y represents the value of update gate, and these two values are gate control signals, then the expression of the input-output relationship of *GRU* is given by the following formulas:

$$\begin{cases} e_y = \delta(Q_e \cdot Z_y + I_e \cdot g_{y-1} + n_e) \\ X_y = \delta(Q_x \cdot Z_y + I_x \cdot g_{y-1} + n_x) \\ S_y = TANg\,(Q_g \cdot Z_y + I_e \cdot (e_y \Phi g_{y-1} + n_g)) \\ g_y = (1 - X_y)\,\Phi g_{y-1} + X_y \Theta S_y \end{cases} \tag{1}$$

The raw data on the learning needs of the smart teaching system were subjected to two-time pattern decomposition and were decomposed into several sub-sequences. In this way, the different patterns and trends in the data could be revealed and captured, allowing the model to accurately capture changes in learning needs at all levels. By creating *GRU* models for each sub-sequence, the models can capture the time dependence and dynamic changes inside each sub-sequence, and the trends of needs in each specific aspect can be figured out better. For the prediction of each sub-sequence, data from the smart teaching system's influencing factors at the previous moment of prediction were collected, combined, and taken as the input of the *GRU*. Such a combination ensures that the model can fully utilize past information and the current state of the environment to make predictions, increasing the accuracy and robustness of the predictions. Then, the predicted values of the smart teaching system of each sub-sequence were combined to get the final learning needs prediction results of the smart teaching system of the *GRU* models. This step gives comprehensive and coordinated learning needs predictions by integrating the information of each sub-sequence, better reflecting the overall situations and dynamics of the learning needs.

2.2 Model of reinforced learning

Figure 1 shows the flow for learning needs prediction of the smart teaching system. The Q-learning algorithm of reinforced learning is known to act as a decision-making engine in the learning needs prediction model. The system's flexibility, effectiveness, and development potential can be enhanced through self-adaption, reward-driven, and long-term exploration mechanisms. Moreover, the integration with deep learning has strengthened the ability to understand and respond to the complex needs of students, laying a solid foundation for realizing personalized smart teaching.

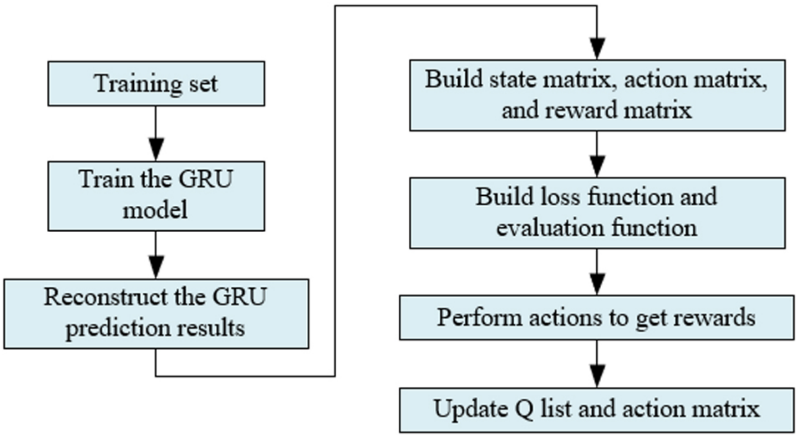

Fig. 1. Flow of learning needs prediction of the smart teaching system

Steps of learning needs prediction of smart teaching system based on the Q-learning algorithm integration method are given below:

1. Construct state matrix, action matrix, and combination model: The state matrix describes the system's possible states. In smart teaching scenarios, the states include students' learning progress, performance, and interactive behaviors. The action matrix defines the actions that the system might perform, such as pushing different-type teaching resources and adjusting learning paths. These two matrices constitute a basic framework for the environment of reinforced learning and define the dynamics of learning progress. The combination model combines the state matrix and action matrix with the deep learning model (such as *GRU*), allowing the system to select the optimal action based on history data and the current state. This step involves the integration of reinforced learning and deep learning so that the prediction process can make use of both the representational learning ability of deep learning and the decision optimization ability of Q-learning.

$$\begin{cases} a = [q_1, q_2, q_3] \\ s = [\Delta q_1, \Delta q_2, \Delta q_3] \\ t = S_1 q_1 + S_2 q_2 + S_3 q_3 \end{cases} \tag{2}$$

Assuming S_1 and q_1 represent the predicted value of the smart teaching system at the initial state (the introductory stage of students) and the weight in the combination; S_2 and q_2 represent the predicted value of the smart teaching system at the intermediate state (the in-progress stage of students) and the weight in the combination; S_2 and q_2 represent the predicted value of the smart teaching system at the advanced state (the deep learning stage or near-completion stage of students) and the weight in the combination; Δq_u represents the weight variation of the prediction results of the deep learning model; for the problem being studied in this paper, the action matrix *s* has two actions *s1* and *s2*, and the state matrix *a* has three states, namely the initial state, the intermediate state, and the advanced state.

2. Construct loss function and reward function: The loss function measures the difference between prediction and actual needs, giving instructions to the optimization of the model. The reward function assigns rewards according to the effect of adopted actions, urging the agent to learn how to choose the action that is the most favorable to the goal. These two functions work together during the training process, making the agent to automatically adjust its strategy to improve prediction accuracy and meet actual needs.

   Assuming b represents the number of input sample point data, $S(l)$ represents the measured data of the learning needs of the smart teaching system, $S'(l)$ represents the predicted data of the learning needs of the smart teaching system, then the loss function M and the reward function E can be constructed as follows:

$$M = \frac{1}{b}\sum_{l=1}^{b}(S(l) - S'(l))^2 \tag{3}$$

$$E = \begin{cases} +1 + M_l - M_{l+1}(M_{l+1} < M_l) \\ -1 + M_l - M_{l+1}(M_{l+1} > M_l) \end{cases} \tag{4}$$

3. Train the agent based on the training set of the established deep learning model. That is, the history data of learning needs and relevant features were adopted to train the agent. During the training process, the agent learns how to choose the optimal action based on current state and environment information, and constantly optimizes its strategy to reduce the loss function and maximize the reward. Figure 2 shows the interaction process between the agent and the environment. The agent would execute an action s according to current state a. Assuming $s_{Q_{MAX}}$ represents the action state corresponding to the optimal value in Q list, s_{RD} represents to randomly take an action state s, σ represents random number between 0 and 1, γ represents the greedy coefficient, then the following formula gives the expression of action selection based on the *ε-greedy* strategy:

$$s_l = \begin{cases} s_{W_{MAX}};(\sigma < \gamma) \\ s_{W_{RD}};(\sigma > \gamma) \end{cases} \tag{5}$$

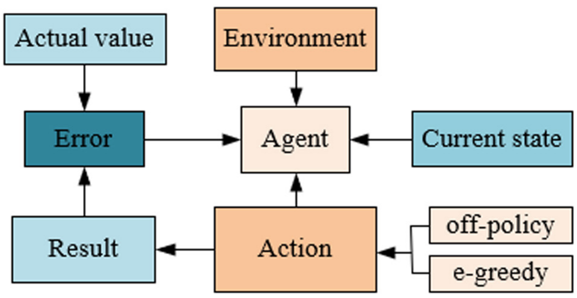

Fig. 2. Interaction process between *Agent* and environment

4. Calculate the loss function to get rewards, and then calculate the evaluation Q function and update the Q list. The Q function represents the expected reward for

taking a particular action under a given state. Calculating Q function and updating Q list are core steps of Q-learning. Through unremitting tries and learning, the Q list gradually converges to the optimal strategy, enabling the system to select the most favorable action for learning needs prediction and satisfaction under various states.

Assuming $W_{OL}(a_l, s_l)$ represents the estimated Q value in case that action s_l is performed under state a_l; $E + \varepsilon MAXW_{OL}(a_{l+1}, s_l)$ represents the actual Q value of $W_{OL}(a_l, s_l)$; $MAXW_{OL}(a_{l+1}, s_{l+1})$ represents the maximum estimated Q value of state $l+1$; s_{l+1} represents the action taken for attaining the maximum Q value; β represents the learning efficiency; ε represents the attenuation coefficient of future rewards; $W_{NE}(a_l, s_l)$ represents the Q value under the condition that action s_l is taken under state a_l; the following formula gives the updated Q value and the state:

$$\begin{aligned} &W_{NE}(a_l, s_l) \leftarrow W_{OL}(a_l, s_l) + \beta\left[E + \varepsilon MAXW_{OL}(a_{l+1}, s_{l+1}) - W_{OL}(a_l, s_l)\right] \\ &a_l \leftarrow a_{l+1} \end{aligned} \tag{6}$$

5. Repeat above two steps until the iteration stop condition has been met.

3 ENHANCEMENT OF THE RESPONSE ABILITY OF SMART TEACHING SYSTEM

Students have different learning needs and interests, and a smart teaching system should be able to accurately identify and understand the individual learning needs of each student with its coherent response ability and provide personalized learning resources and teaching solutions for them in a targeted manner, thereby triggering learning interest in students, enhancing learning initiative, and increasing learning participation. When compared to the conventional one-to-many mode of teaching, a smart teaching system with the ability to respond fluently can conduct deeper-level interactions with students in a more targeted way. This not only enables timely responses to students' questions and needs, but it also deepens and broadens their learning and inspires reflections and explorations through targeted questions and challenges. By continuously analyzing the responses and feedback of students, the smart teaching system can give real-time evaluations on students' learning progress and level of understanding, allowing for timely teaching adjustments. Such flexibility and agility help to ensure that the teaching content matches the actual needs and abilities of students, reducing frustration or stress caused by inappropriate difficulty in teaching. In summary, the ability to give coherent and informative responses based on the features of the learning needs of different students is vital for a smart teaching system.

To this end, this paper developed an encoder-decoder framework that incorporates the retrieval attention mechanism, and a two-stage training method was adopted to improve the response accuracy of consistent content. The model can more accurately retrieve the response content in need from the data table of the key value-style learning needs information of students, and this design can directly reflect the emphasis on the personal learning needs of different students, which is conducive to giving accurate pushing and personalized teaching. The proposed two-stage training method performs pre-training on the general data set and then fine-tuning on the specific learning needs of individual students, significantly improving the model's accuracy and consistency. Moreover, such a staged training method considers the generalization ability and specificity of the model, enabling the model to adapt to different learning scenarios as well as accurately capturing the specific needs of individual students. A schematic of the model structure is given in Figure 3.

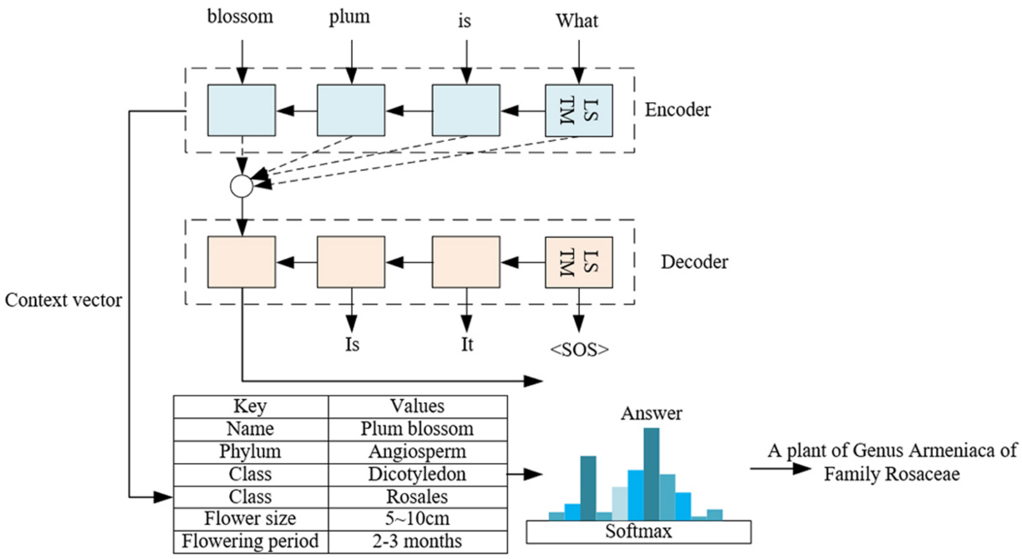

Fig. 3. Model structure

In the model, the *Bi-LSTM* was adopted to perform bi-directional encoding on source sentences, which solved the gradient vanishing problem of sentences with long distance dependencies. Assuming $\vec{g}_y$ and $\overleftarrow{g}_y$ represent the forward and back-forward hidden layer states of each unit; the combination of $\vec{g}_y$ and $\overleftarrow{g}_y$ represents the final hidden state of each word z_y, which is denoted by g_y; d represents a nonlinear mapping function, then there are:

$$\vec{g}_y = d(z_y, \vec{g}_{y-1}) \tag{7}$$

$$\overleftarrow{g}_y = d(z_y, \overleftarrow{g}_{y-1}) \tag{8}$$

$$g_t = \left[\vec{g}_t + \overleftarrow{g}_t\right] \tag{9}$$

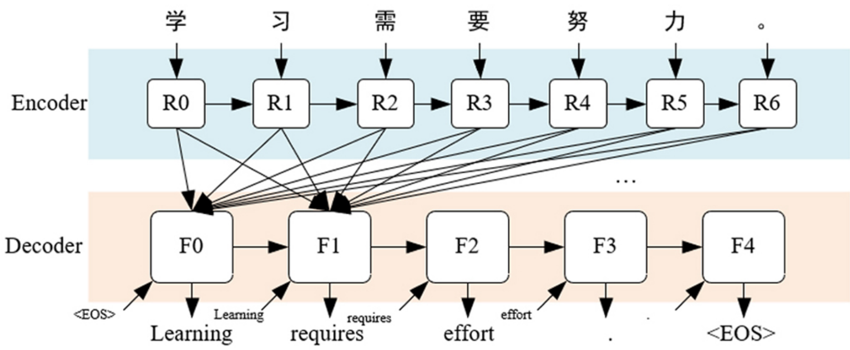

Fig. 4. The introduced attention mechanism

Figure 4 gives a schematic showing the introduced attention mechanism. The attention mechanism allows the model to be more flexible in extracting relevant content from the huge information base of students' learning needs, and this ability for dynamic acquisition and matching greatly enhances the model's adaptability to complex and changing needs. Such an attention mechanism makes the model more sensitive to students' individual needs, so that more accurate responses could be provided to these needs. Therefore, during the encoding process, a weighted context matrix v_u was built based on dynamic weight. Assuming: a_u and g_u represent the hidden states of the decoding and encoding layers, respectively, and SC represents the neural network model for calculating the score between a_u and g_u, then the calculation process can be written as:

$$v_u = \sum_{k=1}^{Y} s_{u,k} g_k \tag{10}$$

$$s_{u,k} = \frac{\exp(SC(a_{u-1}, g_k))}{\sum_{j=1}^{Y} \exp(SC(a_{u-1}, g_j))} \tag{11}$$

According to the different calculation methods of SC, namely the point-wise multiplication, common point-wise multiplication, and vector splicing, the attention-integrated model can be expressed as follows:

$$SC(a_u, g_k) = \begin{cases} a_u^Y g_k \\ a_u^Y Q_s g_k \\ c_s^Y \tanh\left(Q_s \left[a_u^Y; g_k\right]\right) \end{cases} \tag{12}$$

The SC scores were then normalized by the *softmax* function to get the weights corresponding to the hidden states of each layer in the u-th step, represented by $s_{u,k}$, and v_u can be attained through the operation of weighted summation. Assuming $s_{u,k}$ represents the weight of the contribution of a hidden state to the context vector, then the next output of decoder $m_{u,k}$ can be attained based on v_u and a_{u-1}:

$$m_u = \tanh(Q_m[v_u, a_u]) \tag{13}$$

Assuming J represents the dimension of word vector, C represents the number of lexicons, let $Q_m \in R^{J\times 2J}$ and $Q_{PR} \in R^{J\times 2J}$; assuming t_y represents the predicted word generated in the y-th step by the source sentence, then the probability distribution in the case that t_y is known can be calculated by the following formula:

$$o\left(t \middle| t_1, t_2, \cdots, t_{y-1}, z\right) = softmax(Q_{PR} \cdot m_u) \tag{14}$$

Based on the context matrix and the hidden state of previous step, the hidden state of current step can be further calculated by the following formula:

$$a_y = d(a_{y-1}, v_y, t_{y-1}) \tag{15}$$

The decoder can output the word probability distribution of each step sequentially, combining it with other learning resources and tools, such as images, videos, and tests, to provide students with a rich and diverse learning experience. By integrating multiple information sources, the system can provide more comprehensive and multi-dimensional responses, enabling the students to understand and master the knowledge in an all-round way. The decoder adopted a crossover method to calculate the loss between the predicted sequence and the target sequence and dynamically adjust the response strategy according to the responses and feedback input by students in real time, thereby achieving real-time and targeted interactions between students and the system. This dynamic adjustment ability allows the system to capture and adapt to students' learning progress and the changes in their learning needs in a timely manner, thus ensuring the relevance and effectiveness of the responses.

4 EXPERIMENTAL RESULTS AND ANALYSIS

By observing the actual and predicted values shown in Figure 5, situations of the learning needs prediction of the smart teaching system could be analyzed. The predicted values were very close to the actual values for time periods 8:00–11:15 in the morning and 14:30–17:45 in the afternoon, as shown in the figure, indicating that the model was accurate and reliable during these time periods. As for the time period 11:15–14:30 at noon, the predicted values were slightly higher than the actual values at times; the difference was still very small, indicating that the model was very accurate during this time period. According to the overall trend, the fluctuations of the predicted and actual values were highly consistent. Although there were some deviations, on the whole, the trends of prediction and actual condition were very close. The learning needs prediction model of a smart teaching system established based on deep learning (*GRU*) and reinforced learning (Q-learning algorithm) exhibited high accuracy and strong robustness over multiple time periods. The model could capture almost perfectly the trends of actual learning needs, especially in the morning and afternoon hours.

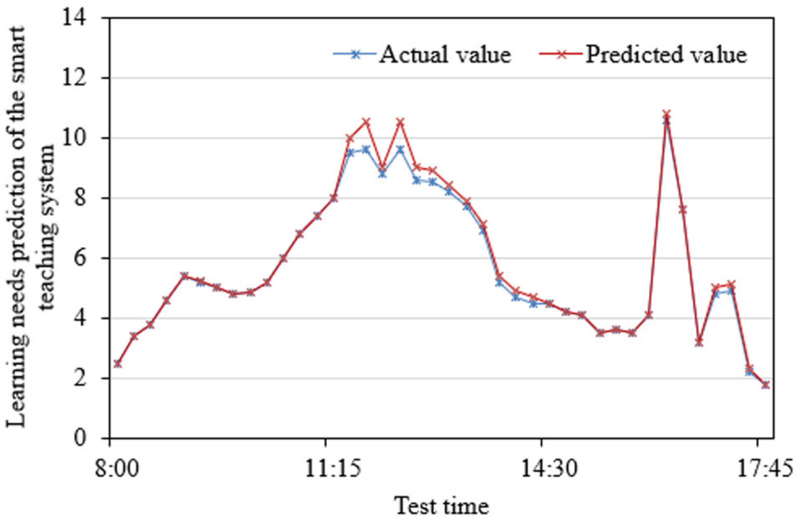

Fig. 5. Curve of learning needs prediction of the smart teaching system

Table 1. Prediction errors of each model in case of different types of student learning needs

Type of Needs	Prediction Model	*MAE*	*RMSE*	*MAPE*
Needs of teaching content	*RNN*	0.451	0.524	5.124
	GRU	0.368	0.364	4.263
	GRU + Q-learning	0.251	0.295	3.265
Needs of operational skills	*RNN*	0.325	0.452	6.354
	GRU	0.315	0.413	5.231
	GRU + Q-learning	0.36	0.482	3.269
Needs of interactions	*RNN*	0.326	0.326	7.234
	GRU	0.255	0.382	5.236
	GRU + Q-learning	0.274	0.233	4.369

Table 1 compares the prediction errors of each model in the case of different types of student learning needs. As shown in the table, in terms of the prediction of students' needs for teaching content, compared with *RNN*, the *GRU* model showed an improvement, and the values of *MAE*, *RMSE*, and *MAPE* were all reduced. The *GRU* model incorporating Q-learning further reduced these error indicators, showing a greater power of prediction. As for the prediction of students' needs for operational skills, the performance of *RNN* and *GRU* was close, and *GRU* had a slight advantage. After Q-learning was introduced, although the values of *MAE* and *RMSE* increased, the value of *MAPE* decreased significantly, indicating better performance in the aspect of percentage error. In terms of the prediction of students' needs for interactions, the error indicators of the *GRU* model were smaller than those of the *RNN*; the *GRU* model incorporating Q-learning had further optimized the *MAPE*, and its *MAE* and *RMSE* values increased slightly. Overall, the proposed learning needs prediction model of a smart teaching system constructed based on deep learning (*GRU*) and reinforced learning (Q-learning algorithm) was effective in the case of all three types of learning needs, especially in aspects of the needs for teaching content and interactions, where the hybrid method significantly outperformed the methods of using *RNN* or *GRU* alone. This conclusion highlights the value of combining deep learning and reinforced learning, it provides useful evidence for the learning needs prediction of smart teaching systems in the future, and helps to give more accurate and personalized support for different types of students.

Table 2. Response accuracy of each model on all test data and on each type of test data

Model	Full	Data of Real Questions	Data of Simulated Questions	Data of Multiple-Choice Questions	Data of Open-Ended Question	Data of Dialogues	Data of Hybrid Difficulties
CNN	17.6	11.5	26.3	18.2	11.5	28.9	18.9
LSTM	23.5	19.4	22.4	16.9	18.6	33.6	22.4
GAN	44.1	58.7	43.8	32.5	28.6	53.1	42.3
Transformer	52.3	61.2	58.6	38.1	41.2	69.1	57.6
MLP	58.6	69.3	73.1	36.9	43.8	71.5	61.5
The proposed model	56.4	71.2	76.3	42	42.9	42.8	62.8

Table 2 lists the response accuracy of each model on all test data and on each type of test data. As shown in the table, the encoder-decoder framework incorporating the retrieval attention mechanism constructed in this paper performed the best on data of real questions and simulated questions, and it also performed well on data of hybrid difficulties. Although its performance was slightly inferior to that of *Transformer* and *MLP* on the data of dialogues, it performed stably on the full range of test data, proving the effectiveness of the proposed model in enhancing the response ability of the smart teaching system, especially on the data of real and simulated questions. The model exhibited excellent accuracy, proving its powerful capability in comprehending and dealing with questions in real learning scenarios. Compared with other advanced models, the proposed model demonstrated its competitiveness on the full range of tests, especially on the data of hybrid difficulties, showing its outstanding flexibility and robustness in dealing with questions of different types and difficulties.

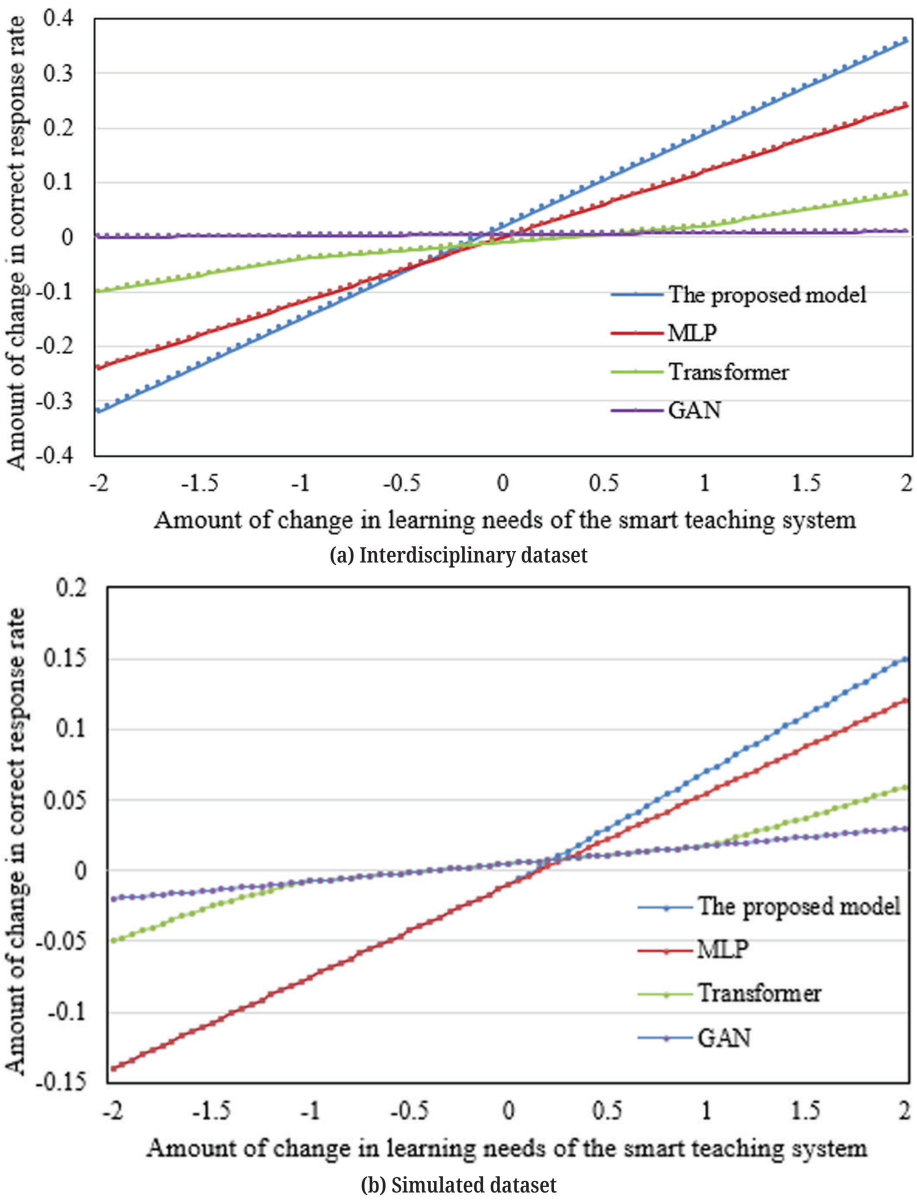

Fig. 6. Comparison of generalization ability of various models on different test datasets

Figure 6 compares the generalization ability of various models on the interdisciplinary dataset and the simulated dataset. In this study, the generalization ability was measured by the trend of the change in the correct response rate with the change in the learning needs of the smart teaching system. As shown in the figure, as the amount of change in learning needs increased, the correct response rate of the proposed model showed a steady and gradual rising trend, indicating that the proposed model can flexibly adapt to different changes in learning needs, and it exhibited outstanding generalization ability. Although the generalization ability of the *MLP* model was relatively stable in some intervals of the amount of change in learning needs, its overall trend was more rigid than the model proposed in this study, and it failed to show flexibility to keep pace with the changes in learning needs. *Transformer* showed medium-level stability in its generalization ability. However, its response to the amount of change in learning needs was still not as sensitive as the proposed model, especially in intervals with large changes in learning needs. The *GAN* model's generalization ability changed very little throughout the entire range, which could indicate that the model was less adaptable to interdisciplinary datasets.

The above analysis suggests that the encoder-decoder framework incorporating the retrieval attention mechanism constructed in this paper exhibits excellent generalization ability. When compared with other models, it showed higher sensitivity and adaptability throughout the entire range of the amount of change in learning needs of the smart teaching system.

5 CONCLUSION

This study focused on the topic of smart teaching systems, especially how to improve the generalization ability of the system using different models and methods. An encoder-decoder framework that incorporates the retrieval attention mechanism was constructed and compared to other models, including *MLP*, *Transformer*, and *GAN*. Through the design of this framework, this paper proposes a new method for coping with changes in the learning needs of smart teaching systems, and the advantages of the new model in generalization ability were demonstrated via comparisons with existing models. The generalization ability of each model was quantitatively evaluated through an analysis of the trend of the amount of change in the correct response rate with the amount of change in the learning needs of the smart teaching system, and the experimental results showed that the proposed model performed more stably in cases of different changes in the needs, and its generalization ability was better.

This study successfully revealed the potential of the encoder-decoder framework incorporated with the retrieval attention mechanism in the application of smart teaching systems. When compared to some existing mainstream models, the new model exhibited a significant advantage in generalization ability. This finding not only provides new perspectives and methods for further research on smart teaching systems, but it also provides useful reference on how to select and construct more effective models in practical applications. The experimental results also demonstrated that the adaptability and generalization performance of the model can be significantly improved by a well-designed attention mechanism, paving the way for the future development of smart teaching systems.

6 ACKNOWLEDGEMENT

This paper was supported by China Foundation for Youth Entrepreneurship and Employment (Grant No. 2023A01-01) and Hunan Social Science Achievement Review Committee (Grant No. No912).

7 REFERENCES

[1] P. Adamec, "Teaching vocational subjects in secondary school: A new career or a backup plan?" *International Journal of Engineering Pedagogy*, vol. 13, no. 5, pp. 142–160, 2023. https://doi.org/10.3991/ijep.v13i5.37555

[2] D. Kang and B. Zhang, "The feasibility of practical vocational education in higher education institutions," *International Journal of Emerging Technologies in Learning*, vol. 17, no. 14, pp. 94–108, 2022. https://doi.org/10.3991/ijet.v17i14.32811

[3] Y. Y. Kuang and Z. W. Li, "Personal value orientation, expectation confirmation and choice behavior: A perspective of sustainable higher vocational development," *International Journal of Sustainable Development and Planning*, vol. 17, no. 7, pp. 2263–2270, 2022. https://doi.org/10.18280/ijsdp.170727

[4] J. Song, "Application analysis of big data technology in vocational education informatization," in *International Conference on Frontier Computing*, Seoul, Korea, 2022, pp. 895–900. https://doi.org/10.1007/978-981-99-1428-9_112

[5] A. M. Nidhom, A. B. N. R. Putra, A. A. Smaragdina, G. D. K. Ningrum, and J. M. Yunos, "The Integration of augmented reality into MOOC's in vocational education to support education 3.0," *International Journal of Interactive Mobile Technologies*, vol. 16, no. 3, pp. 20–31, 2022. https://doi.org/10.3991/ijim.v16i03.28961

[6] K. A. Ogbonnaya and O. E. Ann, "Enhancing women's participation in community development through community education for sustainable development in South-East Nigeria," *International Journal of Sustainable Development and Planning*, vol. 18, no. 7, pp. 2293–2300, 2023. https://doi.org/10.18280/ijsdp.180734

[7] M. Muchlas, P. Budiastuti, M. Khairudin, B. Santosa, and B. Rahmatullah, "The use of personal learning environment to support an online collaborative strategy in vocational education pedagogy course," *International Journal of Interactive Mobile Technologies*, vol. 17, no. 2, pp. 24–41, 2023. https://doi.org/10.3991/ijim.v17i02.34565

[8] J. Wang and J. Liu, "Effects of a new media data interaction system on teaching efficiency in vocational education," *International Journal of Emerging Technologies in Learning*, vol. 17, no. 7, pp. 163–174, 2022. https://doi.org/10.3991/ijet.v17i07.30457

[9] O. Zhukova, V. Mandragelia, T. Alieksieienko, A. Semenenko, and E. Skibina, "Digital technologies for introducing gamification into the education system in the context of the development of industry 4.0," *Ingénierie des Systèmes d'Information*, vol. 28, no. 1, pp. 141–147, 2023. https://doi.org/10.18280/isi.280114

[10] L. Li, "Scale evolution of higher vocational education and measurement of education opportunity difference based on the expansion effect," *International Journal of Emerging Technologies in Learning*, vol. 18, no. 2, pp. 245–260, 2023. https://doi.org/10.3991/ijet.v18i02.37137

[11] G. Gabrhelová, M. Matulčíková, E. Dolinská, S. Barnová, and D. Breveníková, "Professional corporate employee education from the point of view of the types of education and the applied forms of education," *International Journal of Engineering Pedagogy*, vol. 13, no. 2, pp. 4–19, 2023. https://doi.org/10.3991/ijep.v13i2.34799

[12] S. Wu, X. Xu, R. Liu, G. Liang, H. Meng, and B. He, "An intelligent tutoring system for math word problem solving with tutorial solution generation," in *International Conference on Intelligent Education and Intelligent Research (IEIR)*, Wuhan, China, 2022, pp. 183–188. https://doi.org/10.1109/IEIR56323.2022.10050083

[13] S. Singh and V. Singh, "An architecture of domain independent and extensible intelligent tutoring system based on concept dependencies and subject paths," *International Journal of Advanced Computer Science and Applications*, vol. 13, no. 5, pp. 320–329, 2022. https://doi.org/10.14569/IJACSA.2022.0130538

[14] J. T. Purba, S. Budiono, E. S. Hariandja, and R. Pramono, "Sustainability strategy to alleviate poverty through education, energy, GRDP, and special funds: Evidence from Indonesia," *International Journal of Sustainable Development and Planning*, vol. 18, no. 5, pp. 1397–1406, 2023. https://doi.org/10.18280/ijsdp.180510

[15] Y. Fang, A. Lippert, Z. Cai, S. Chen, J. C. Frijters, D. Greenberg, and A. C. Graesser, "Patterns of adults with low literacy skills interacting with an intelligent tutoring system," *International Journal of Artificial Intelligence in Education*, vol. 32, no. 2, pp. 297–322, 2022. https://doi.org/10.1007/s40593-021-00266-y

[16] N. J. Ahuja, M. Thapliyal, A. Nayyar, and A. Kumar, "Designing of learning environment of an intelligent tutoring system for academic learning needs of learning-disabled learners based on survey report of region-specific target group," *Emerging Technologies for Computing, Communication and Smart Cities*, pp. 389–404, 2022. https://doi.org/10.1007/978-981-19-0284-0_29

[17] G. Rebolledo-Mendez, N. S. Huerta-Pacheco, R. S. Baker, and B. du Boulay, "Meta-affective behaviour within an intelligent tutoring system for mathematics," *International Journal of Artificial Intelligence in Education*, vol. 32, pp. 174–195, 2022. https://doi.org/10.1007/s40593-021-00247-1

[18] R. Zhao, H. Siy, C. Pack, L. K. Soh, and M. Song, "An intelligent tutoring system for api misuse correction by instant quality feedback," in *IEEE 46th Annual Computers, Software, and Applications Conference (COMPSAC)*, Alamitos, CA, USA, 2022, pp. 123–128. https://doi.org/10.1109/COMPSAC54236.2022.00026

8 AUTHORS

Yijiao Sun is a graduate of Hunan University of Chinese Medicine, specializing in vocational education and maternal-child nursing research (E-mail: Sunyijiao0803@163.com; ORCID: https://orcid.org/0009-0002-5450-1049).

Wei Huang holds a Master's degree in medicine from Central South University, with a research focus on vocational education and elderly care (E-mail: ycc161118@163.com; ORCID: https://orcid.org/0009-0003-0189-7817).

Zhiwen Wang holds a Master's degree in medicine from Wuhan University, with a research focus on vocational education (E-mail: wzw189189@wust.edu.cn; ORCID: https://orcid.org/0009-0000-4637-2449).

Xiaofeng Xu holds a Master's degree in medicine from Xuzhou Medical University, specializing in vocational education and elderly care research (E-mail: xuxiaofeng2008107@126.com; ORCID: https://orcid.org/0009-0009-2874-4769).

Min Wen holds a Master's degree in medicine from the University of South China, specializing in vocational education and elderly care research (E-mail: wm148401@163.com; ORCID: https://orcid.org/0000-0003-1153-9952).

Pei Wu holds a Master's degree in medicine from the University of South China, with a research focus on vocational education and elderly care (E-mail: Wupei0303@163.com; ORCID: https://orcid.org/0009-0006-1605-7687).