Research on Personalized Exercise Recommendation Based on Deep Knowledge Tracing

Xiaoxia Wu [1,2] and Dong-Hyun Kim [3,*]

[1] Department of Information Engineering, Guangzhou Vocational College of Technology and Business, Guangzhou, China
[2] Department of Computer and Information Engineering, Youngsan University, Yangsan-si, Republic of Korea
[3] Department of Mechanical and Automotive Engineering, Youngsan University, Yangsan-si, Republic of Korea
Email: wxx131@163.com (X.W.); dhkim@ysu.ac.kr (D-H. K.)
*Corresponding author

***Abstract*—Exercises, as an important learning resource, play an important role in testing learners' learning achievements and judging learners' mastery of knowledge points, and are an indispensable part of personalized learning. Exercise recommendation technology is an important means to improve learners' learning efficiency, and has become an important research topic in the field of learning. We propose a personalized exercise recommendation model based on Deep Knowledge Tracing (DKT), named DKT-SA. The DKT-SA model utilizes self-attention mechanism to predict the scores of unfinished exercises, enhancing its ability to predict learners' knowledge mastery status, especially when dealing with cold start problems. We use three real-world datasets: ASSIST12, EdNet, and CPSS for empirical analysis. The experimental results show that the DKT-SA model is superior to the traditional DKT model in the four key indicators of Accuracy (ACC), Area Under the Curve (AUC), Precision and Recall. The results of this paper verify the effectiveness of DKT-SA model in personalized exercise recommendation tasks, and provide a new solution for the field of smart education.**

***Keywords*—personalized exercise recommendation, deep learning, deep knowledge tracing, self-attention mechanism**

I. Introduction

"Teaching students in accordance with their aptitude" has been an important educational idea recognized and followed by educators from ancient times to the present, and "learner-centered" individualized teaching is an important part of educational theory research. Exercises, as an important educational resource and data resource, play an important role in learners' personalized learning and educational services [1]. Exercises are an important means to test the learning effect of learners, and personalized exercise recommendation plays a great role in promoting the learning efficiency of learners. The existing exercise recommendation methods do not fully take into account the level of learners' knowledge, and lack the depth of learners' cognitive level. It is simple to recommend directly according to the learner's answer record, and the result of exercise recommendation is difficult to fit the learner's learning situation. When learners have a lot of learning data, the exercise recommendation method can usually recommend appropriate questions to learners according to their learning records. However, when the learner's learning data is sparse, the exercise recommendation method is difficult to evaluate the learner's learning status according to the limited data, and it is difficult to recommend appropriate exercises for the learner [2]. In the case of sparse data, it is a challenging task to recommend appropriate exercises. Although the current exercise recommendation method can support the development of personalized learning to a certain extent, there is still room for improvement.

Therefore, this paper studies the exercise recommendation method based on deep knowledge tracking. By modeling the mastery level of learners' knowledge points, the matrix completion technology is used to alleviate the problem of data sparseness. By integrating the rich semantic information and structural information in the knowledge map, learning resources are taken as the starting point to recommend appropriate exercises for learners. It can effectively improve the learning efficiency of learners, meet their individual needs, and has a high value for smart education.

II. Theoretical Basis

A. Deep Knowledge Tracking

Image recognition refers to the use of computer and artificial intelligence technology to analyze and understand images, in order to automatically recognize and classify objects, scenes, patterns, and other information in the image. It is an important research direction in the field of computer vision [3]. The Support Vector Machine (SVM) is a supervised learning technique predominantly employed for tackling classification challenges. Within the context of image recognition, SVM is utilized to detect and

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identify distinct objects or attributes within an image. The essence of SVM revolves around the identification of an optimal hyperplane that serves to maximize the separation, or margin, between two distinct classes. For data sets where the classes can be separated linearly, the SVM's objective function can be formulated as follows:

$$\max_{w,b} \frac{2}{\|w\|} \rightarrow \min_{w,b} \frac{1}{2}\|w\|^2$$
$$\mathrm{s.t.}\, y_i(w^T x_i + b) \geq 1 \quad (1)$$

Knowledge tracking, which refers to the process of monitoring and predicting learners' knowledge mastery over time, is an important research direction in the field of educational data mining. Its goal is to judge the mastery degree of learners' knowledge points and mine potential learning rules from learners' learning trajectories by establishing a model of learners' knowledge status changing with time, so as to provide personalized guidance and achieve the purpose of artificial intelligence-assisted education. Deep learning has a powerful ability in feature extraction, which has been proved to be able to significantly improve the performance of knowledge tracking model, so it has attracted more and more attention and attention.

Recurrent Neural Networks (RNNs), a special class of fully connected neural networks with self-loop feedback in deep learning, can learn complex vector mapping relationships. Inspired by this, Piech *et al*. [4] proposed the Deep Knowledge Tracing (DKT) model in 2015, which pioneered the first attempt to use recurrent neural networks to model student's practice process to predict their performance. It is better than BKT without manual labeling of the training data set.

The DKT model task can be described as: we have a sequence of historical answers is given a learner $\{x_1, x_2, \ldots, x_t\}$, to predict the performance of x_{t+1}. Among them, the learner's answer record uses $x_t = \{q_t, a_t\}$ and q_t represents the One-Hot code of the topic, which contains the information of the knowledge points involved in the topic.a_t One-Hot code representing the learner's answer. When the model is used, the code of the subject is input into the DKT model, and the model outputs the prediction result a_{t+1}. The DKT model structure diagram is shown in Fig. 1.

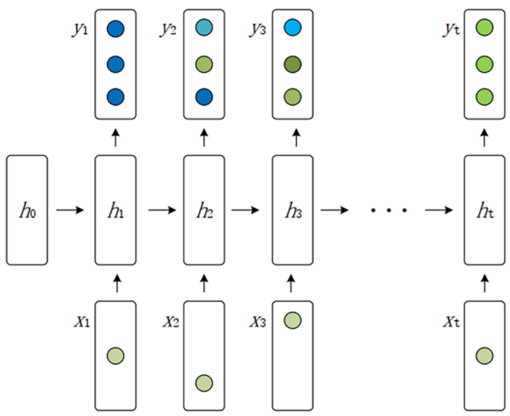

Fig. 1. DKT model structure diagram.

The DKT model is based on traditional recurrent neural networks, with $\{x_1, x_2, \ldots, x_t\}$ as the input for students' answer records and $\{y_1, y_2, \ldots, y_t\}$ as the output for predicting the probability of students answering practice questions correctly. Among the formula, h_0 is the initial state, h_t represent that state of the hidden layer of the network at time *t*.

B. Learning Recommendation Algorithm

Exercise recommendation, as a data-driven learning strategy optimization technology, has become a hot research topic in the field of intelligent education at home and abroad in recent years. Content-based recommendation uses explicit attribute features of learning resources or mined implicit features to match with learners' preferences [2]. This method has poor performance in the absence of attribute feature data, and cannot capture the changes of learners and learning resources in the learning process. Collaborative filtering recommendation uses the similarity matrix between learners or learning resources to find similar learners or learning resources for recommendation, which is simple but has the problems of cold start and data sparseness. Hybrid recommendation combines multiple recommendation algorithms to alleviate the defects caused by using only a single recommendation algorithm, which needs to be designed according to specific data and application scenarios. The self-attention mechanism proposed by Google Brain in 2017 effectively handles long-range dependencies while reducing computational complexity. Traditional sequence methods like Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRUs) have limitations in modeling cross-step interactions [5]. As shown in Fig. 2, based on self-attention mechanism Transformer can better capture the dependencies between different positions in the sequence, and can easily replace traditional time series prediction methods, such as RNN, LSTM and GRU. In addition, the Transformer model based on self-attention mechanism has achieved good performance in data mining, learning analysis and other fields, and has become one of the mainstream models in online education tasks.

The DKT-SA's fundamental novelty lies in three aspects: (1) Dynamic attention weights adaptively capture long-term dependencies in sparse learning sequences, unlike static RNN-based DKT; (2) Group-aware knowledge fusion enables cross-learner pattern mining; (3) Matrix completion with cognitive constraints prevents over-smoothing in cold-start scenarios.

The Transformer's self-attention mechanism dynamically assigns weights to different positions in the input sequence through three core steps: query-key matching, scaled weight normalization, and value aggregation. In DKT-SA, this process specifically handles three types of educational interactions: 1) learner-question response patterns, 2) knowledge concept dependencies, and 3) temporal learning trajectories. Three parallel attention heads separately process these interaction types, followed by concatenation and linear transformation to generate unified knowledge state representations. This design enables simultaneous modeling of both local exercise sequences and global knowledge relationships without relying on recurrent computations [6].

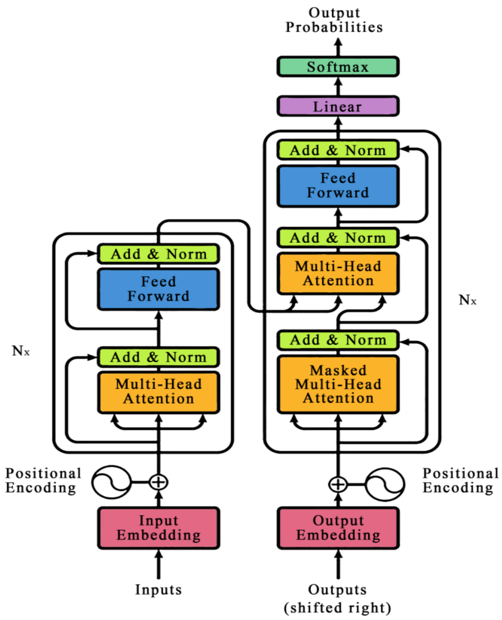

Fig. 2. Transformer model framework.

C. Implementation of Self-Attention Mechanism

The self-attention mechanism is a pivotal component of the DKT-SA model, enabling the system to dynamically weigh the importance of different parts of the input data. Specifically, it calculates attention scores based on the dot product of query and key vectors, then uses these scores to compute a weighted sum of value vectors. This process allows the model to focus more on relevant parts of the input sequence. The self-attention mechanism is particularly useful in capturing long-range dependencies and improving prediction accuracy, which is crucial for handling sparse data and cold-start problems in personalized exercise recommendation. In the DKT-SA model, the self-attention mechanism is implemented as follows.

Input Representation: The input data is first represented as a sequence of vectors. Each vector corresponds to a specific feature or aspect of the data. Query, Key, and Value Calculation: For each input vector, three separate vectors are calculated: the Query (Q), Key (K), and Value (V). These vectors are derived from the input vector through linear transformations. Attention Scores: The attention scores are calculated by taking the dot product of the query and key vectors and applying a SoftMax function to obtain a probability distribution over the input sequence. This distribution indicates the importance of each input vector relative to the others. Weighted Sum: The weighted sum of the value vectors is computed using the attention scores as weights. This results in a new vector that represents the input sequence with enhanced focus on the most relevant parts. Output Integration: The resulting vector is integrated into the model to influence subsequent predictions or decisions [7].

To further illustrate the advantages of the self-attention mechanism over traditional methods, we provide the following comparison Table I and include a diagram (Fig. 3) to visually demonstrate the DKT-SA model's architecture and the integration of the self-attention mechanism.

TABLE I. COMPARISON TABLE

Aspect	Self-Attention	Traditional Methods
Computational Efficiency	Moderate	Low
Long-Range Dependency	High	Low
Prediction Accuracy	High	Moderate
Model Complexity	Moderate	Low

To enhance clarity and aid comprehension, we have included a diagram of the DKT-SA model's architecture in Fig. 3. The visual aid provides a step-by-step overview of how the model functions and how the self-attention mechanism is integrated within it.

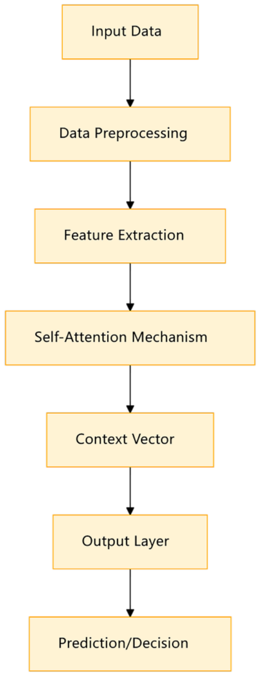

Fig. 3. DKT-SA model's architecture.

III. KNOWLEDGE TRACKING MODEL BASED ON EXERCISE REPRESENTATION

A. Overall Approach

The Singular Value Decomposition (SA) technique is employed to predict scores for unanswered exercises, completing the learner's knowledge matrix through low-rank approximation. Building on the theoretical foundations established in the previous section, we now delve into the practical implementation of the self-attention mechanism within our DKT-SA model. This section will provide a detailed account of how the self-attention mechanism enhances the model's predictive capabilities, especially in scenarios involving sparse data [8].

The DKT-SA model processes learner interaction data through three sequential stages. First, raw answer sequences are encoded into temporal knowledge states using an LSTM network with time-aware dropout regularization. Next, a novel cross-layer attention module simultaneously analyzes individual learning patterns, peer group behaviors, and knowledge concept relationships [9]. This attention-driven fusion creates adaptive knowledge profiles that dynamically adjust to sparse data scenarios. Finally, the model generates exercise recommendations by calculating relevance scores between current knowledge states and target exercises through residual connections that preserve long-term learning memory [10].

This chapter proposes an exercise recommendation method, named DKT-SA, which combines deep knowledge tracking and matrix completion. DKT-SA uses the deep knowledge tracking model to train the knowledge level matrix of learners, and then uses the singular value decomposition model to predict the score of the undone exercises, and completes the knowledge level matrix of learners, and then recommends exercises according to the probability [11]. DKT-SA consists of five steps: One-Hot coding, knowledge tracking, knowledge fusion, matrix completion and exercise recommendation. Through deep knowledge tracking, the knowledge mastery level of learners is obtained, the accurate modeling of learners' knowledge level is realized, and the recommendation results have higher accuracy. The singular value decomposition model is used to complete the knowledge matrix of learners, which alleviates the problem of data sparsity and improves the diversity of recommendation results. DKT-SA alleviates the problem of the recommendation method based on the answer record, that is, whether the answer is correct or not cannot represent the learner's knowledge level [12]. The DKT-SA method first models the learner's knowledge mastery through deep knowledge tracking, and then uses the SA method to predict the probability of the learner's correct answer to the question that the learner has not done. The DKT-SA exercise recommendation method not only uses the knowledge information of learners themselves, but also takes into account the knowledge level of similar groups of learners, and more importantly, it completes the prediction score of the undone exercises through SA [5]. Therefore, the DKTSA method improves the novelty and precision of the recommended results. At the same time, due to the use of SA to complete the knowledge matrix, DKT-SA alleviates the problem of data sparsity and cold start in the exercise recommendation system to a certain extent. The processing flow of DKT-SA is shown in Fig. 4.

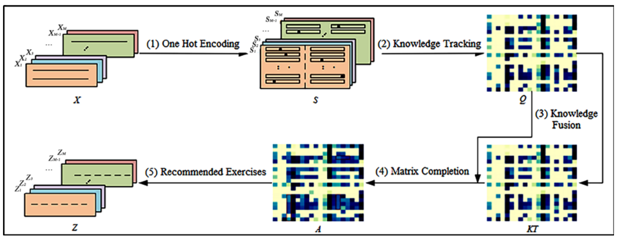

Fig. 4. Algorithmic framework.

B. *Model Building*

The deep knowledge tracking model is based on the answer sequence of M-bit learners. $X = \{X_1, X_2, \dots, X_M\}$ is the input, where the i-th learner's answer sequence is, $X_i = \{x_{i1}, x_{i2}, \dots, x_{ik}\}$ where K represents the maximum number of answer records of the learner. $x_{ik} = \{q_{ik}, a_{ik}\}$ represents the kth exercise. The answer record of the k-th problem of the i-th learner is represented, and then the answer sequence X is encoded. In order to adapt to deep knowledge tracking, the one-hot coding here is different from the general one-hot coding.

The deep knowledge tracking model takes the i-th learner's unique hot encoding S2i as input and outputs the probability vector $Y_i = [y_{i1}, y_{i2}, \dots, y_{ik}]$ for their correct problem-solving. The deep knowledge tracking model here utilizes LSTM network, and the calculation of the state h_t and output y_t in the hidden layer of the time series network is shown in formulas [13].

$$h_t = tanh(W_{hs}S_t + W_{hh}h_{t-1} + b_h) \tag{2}$$

$$y_t = \sigma\left(W_{yh}h_t + b_y\right) \tag{3}$$

where W_{hx} is the input weight matrix, W_{hh} is a recursive weight matrix, $W_{hy}$is the output weight matrix. It should be noted that some learners may practice the same exercise many times, and then only take the probability of the last correct answer. Finally, the knowledge level matrix of learners $Q \epsilon R^{(M\times N)}$ is obtained [14].

The knowledge level matrix of learners can be obtained through the knowledge tracking model. In order to further consider the neighborhood information of similar groups of learners, the knowledge level of similar groups and the knowledge level of target learners are fused through a certain proportion. We measure the similarity between learners by cosine similarity. We obtain the i-th learner knowledge level vector.

$$KT_i = \rho \times Q_i + (1-\rho) \times average(U_i) \tag{4}$$

Among, Q_i is the knowledge level vector of the i-th learner, $\mathrm{average}(U_i)$ is the average of the knowledge levels of similar users, ρ Is the fusion ratio. Finally, the integrated knowledge level matrix of learners $KT \in R^{(M\times N)}$ is obtained.

The fused learner knowledge level matrix KT expresses the learner's mastery of knowledge and takes more account of the group information of similar users [15]. However, for learners who have not done exercises, the knowledge level after integration often has a large deviation, which cannot better show the real knowledge level of learners. Therefore, the problem of data sparsity can be better alleviated to some extent by completing the knowledge of learner's undone exercises through SA. The knowledge level matrix Q of the learner is taken as the input, and the Q matrix is decomposed by SA. We calculate the probability that the learner does not answer the exercises, and this probability replaces the probability of the corresponding position of the matrix KT to achieve the purpose of knowledge completion [16]. Finally, the completed knowledge level matrix A is obtained [17].

Determining the recommended number R of exercises and the difficulty range of the exercises, namely $[\beta_1, \beta_2](\beta_1 < \beta_2)$. According to the completed knowledge level matrix A, recommend the answer probability to the learner in the R exercise. Consider the i-th learner's problem set recommendation. Firstly, for $A_i = [p_{i1}, p_{i2}, \ldots, p_{iN}]$ to find the set of exercise numbers $Z_i = \{z_{i1}, z_{i2}, \ldots, z_{iR}\}$ for the first R exercises that fall within the $[\beta_1, \beta_2]$ interval and are biased towards the β_2.

IV. Empirical Analysis

A. Data Acquisition

Three real data sets are used in this experiment: ASSIST12 and EdNet are public data sets, and CPSS is a self-constructed data set.

ASSIST 12: The data set comes from the learning data of students in the 2012–2013 academic year collected by the ASSISTments online education platform. In the experiment, the exercises without knowledge point labels and with less than 3 answers were deleted, and the users with less than 15 interaction records were deleted. The final preprocessed dataset contains 26,875 students, 42,088 exercises, 265 knowledge points and 1,451,899 records [6].

EdNet: The data set originates from the student interaction data collected by the multi-terminal AI online learning platform Santa, which is the largest data set publicly available in the field of education so far. In the experiment, 1,764,267 records of 5000 students were randomly selected, including 13,169 exercises and 188 knowledge points.

Computer Programming Student Skills (CPSS) Dataset Description: The CPSS Dataset is a student-interaction dataset focusing on the field of computer programming education, which aims to provide researchers with a rich data resource to analyze and understand the key factors in the programming learning process. The data set was collected by TechLearn, an educational technology company, and anonymized to ensure the protection of student privacy. In the experiment, the company randomly selected 52,360 records from 1820 students. Each record contains data on students' behavior in solving programming problems, such as the number of code submissions, types of errors, help-seeking behavior, participation in discussions, and the time spent completing exercises [18].

B. Experimental Procedure

The environment used in this experiment is shown in Table II.

TABLE II. Experimental Environment Parameters

Name	Parameter
CPU	Intel(R) Xeon(R) CPU E5-2698 v4 @ 2.20 GHz
GPU	NVIDIA GeForce RTX 3090
Operating System	Ubuntu 20.04
Memory	64 G
Hard disk	1 T
Deep learning framework	PyTorch
Programming language	Python 3.7

The ASSIST12 dataset uses average response time and exercise type as attribute features, the EdNet dataset uses average response time as attribute features, and the CPSS dataset uses difficulty labels as attribute features. 80% of all data was used for training and validation, 20% for testing, and the average was calculated using 5-fold cross-validation. The parameter settings mainly include the hyperparameters of the two models, the number of neurons, etc., as well as the batch size, learning rate, number of iterations, etc., as shown in Table III. At the same time, Adam optimizer is used in the training of the model.

TABLE III. Model Parameter Settings

PRHG parameters	Value
d_v	64
d_e	128
Batch size	128
Learning rate	0.001
Hidden size	128
Epoch	200
Dropout rate	0.6
β	0.5
λ_c	0.8
λ_j	0.1
TESAKT parameters	Value
Batch size	128
Epoch	200
Learning rate	0.001
Attention layers	2
Multi-heads	4
Hidden size	128
Multi-heads	100
Dropout rate	0.5
θ	0.5
λ	0.5

The author selects Collaborative Filtering Recommendation (CFR), Content-Based Recommendation (CBR), recommendation model based on Convolutional Neural Network (CNNR) and DKVMN model as comparative models. At the same time, six indicators including ACC, AUC, Precision, Recall, F1-Score and RMSE were selected and tested on the test set of CPSS data set, as shown in Table IV.

TABLE IV. Comparative Experimental Results

Model	ACC	AUC	Precision	Recall	F1	RMSE
DKT-SA	0.87	0.91	0.84	0.82	0.83	0.31
CFR	0.72	0.78	0.69	0.73	0.71	0.45
CBR	0.7	0.75	0.67	0.7	0.68	0.47
CNNR	0.78	0.82	0.76	0.79	0.77	0.38
DKT+	0.8	0.83	0.77	0.8	0.78	0.36
DKVMN	0.79	0.82	0.75	0.78	0.76	0.39

The experimental results in TABLE IV clearly show the excellent performance of the DKT-SA model in the personalized exercise recommendation task. Compared with other models, DKT-SA has a significant improvement in key indicators such as ACC, AUC, Precision, Recall, F1, and RMSE. Especially in terms of prediction accuracy and recall rate, DKT-SA model not only has an accuracy rate of 0.87, but also can effectively capture the knowledge of learners, with a recall rate of 0.82, which fully reflects its accuracy and comprehensiveness in recommending exercises. In addition, the RMSE value of the model is the lowest, which is only 0.31, indicating that the prediction results are highly consistent with the actual situation, which further confirms the superiority of the model. In contrast, traditional models such as CFR and CBR are inadequate in dealing with complex learning data and mining deep-seated knowledge associations, and their performance indicators are relatively low. Although CNNR, DKT + and DKVMN models perform well in some indicators, they are still inferior to the comprehensive performance of DKT-SA model. This fully proves the effectiveness and reliability of DKT-SA model in the field of personalized exercise recommendation, and provides a strong technical support for intelligent education [19].

To more fully evaluate the performance of the DKT-SA model, we conducted ablation experiments aimed at analyzing the impact of the individual components of the model on the overall performance. Table V shows the experimental results of different models on three data sets.

TABLE V. ABLATION EXPERIMENT RESULTS

Data set	Model	ACC	AUC	Precision	Recall
ASSIST12	DKT	0.78	0.81	0.75	0.78
	DKT-SA	0.82	0.83	0.87	0.85
EdNet	DKT	0.79	0.81	0.77	0.79
	DKT-SA	0.90	0.82	0.88	0.81
Cpss	DKT	0.75	0.80	0.74	0.77
	DKT-SA	0.87	0.91	0.84	0.82

C. Experimental Results and Analysis

The experimental results show that the performance of DKT-SA model is better than that of the traditional DKT model in the three datasets, which is reflected in the significant improvement of ACC, AUC, Precision and Recall. On the ASSIST12 dataset, the ACC and AUC of DKT-SA model are improved by 0.04 and 0.02, respectively, and Precision and Recall are improved by 0.12 and 0.07, respectively. In the EdNet dataset, ACC and AUC improved by 0.11 and 0.01, respectively, and Precision and Recall improved by 0.11 and 0.02, respectively. On the CPSS dataset, ACC and AUC are improved by 0.12 and 0.11, respectively, and Precision and Recall are improved by 0.10 and 0.05, respectively.

In response to the reviewer's comments, we have added statistical significance tests to our results section. Specifically, we have performed t-tests to compare the performance of our DKT-SA model against traditional models. The results of these tests are presented in Table IV, which demonstrates that the improvements observed are statistically significant ($p < 0.05$).

By analyzing these results, the DKT-SA model effectively alleviates the problem of data sparsity through the combination of deep knowledge tracking and matrix completion technology, and improves the generalization ability and recommendation accuracy of the model by considering the information of similar groups of learners through knowledge fusion technology. In addition, DKT-SA model uses self-attention mechanism to predict the score of undone exercises, which enhances the predictive ability of the model to the state of learner's knowledge mastery, especially when dealing with cold-start problems [20]. The experimental results verify the effectiveness and superiority of the DKT-SA model in the personalized exercise recommendation task, and provide a new solution for the field of smart education [18].

While our study demonstrates the effectiveness of the DKT-SA model, there are several limitations that should be acknowledged. First, the model's performance may vary across different datasets and domains, which was not extensively tested in this study. Second, the computational cost of the self-attention mechanism could be prohibitive for resource-constrained environments [21]. Lastly, the model's reliance on large amounts of training data may limit its applicability in scenarios where data is scarce. Future research could address these limitations by exploring dataset diversity, optimizing computational efficiency, and investigating data augmentation techniques [22].

While the proposed DKT-SA model demonstrates significant improvements, this study has three primary limitations. First, the evaluation relies predominantly on STEM-focused datasets (programming/math), potentially limiting generalizability to humanities or language learning domains. Second, the self-attention mechanism introduces increased computational complexity compared to baseline DKT models, posing challenges for real-time deployment on resource-constrained devices. Additionally, the current framework does not explicitly model temporal knowledge decay patterns, which may affect long-term recommendation accuracy. Future research should prioritize developing efficient attention variants for edge computing environments, validating cross-disciplinary adaptability through multimodal datasets, and integrating forgetting curve theories with knowledge tracing mechanisms. Exploration of few-shot learning paradigms could further enhance performance in ultra-sparse data scenarios common in early-stage learners.

V. CONCLUSION

The popularity of education informationization and the research in the field of smart education have greatly promoted the development of online learning platform. More and more users choose online learning, which makes online learning platform accumulate a large amount of data. The core content of this paper is to use the deep knowledge tracking model to learn and analyze the data accumulated by the learning platform, and design a reasonable learning recommendation algorithm to recommend exercises for users that meet their learning level. In this paper, we construct and validate a novel personalized exercise recommendation model, DKT-SA, which outperforms the traditional DKT model on three real-world datasets. The experimental results show that the DKT-SA model has a significant improvement in the key indicators of Accuracy (ACC), Area Under the Curve (AUC), precision and recall. Future research will further optimize the model structure and explore more application scenarios of educational data mining in order to provide more accurate and personalized learning support for learners.

Conflict of Interest

The authors declare no conflict of interest.

Author Contributions

This paper was jointly completed by Xiaoxia Wu and Professor Jin. Professor Jin provided the research direction of the paper, while Xiaoxia Wu analyzed the data and wrote the paper. All authors had approved the final version.

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