

PAPER

The Role of Mobile Education Technology in Promoting Personalized Learning in Higher Education

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With the continuous development of information technology, mobile education technology has gradually gained widespread application in higher education, driving the realization of personalized learning. Personalized learning aims to provide customized learning content and methods based on students' individual needs, interests, and learning progress, making it an important trend in modern education. However, the challenge of accurately recommending the most suitable learning resources to students through technological means remains a key research issue. In recent years, researchers have proposed various personalized learning recommendation systems, but most studies have not fully explored the complex correlations and nonlinear features in students' learning behaviors, resulting in suboptimal recommendation accuracy and adaptability. Graph neural networks (GNNs), as an emerging deep learning method, have demonstrated superior performance in multiple fields due to its powerful capability to model node relationships. Personalized recommendation systems based on GNN can effectively capture interactions among learners and complex learning needs, offering more precise recommendations for learning resources. This paper aims to explore how lightweight GNN techniques can enhance the performance of personalized learning recommendation systems in higher education. Specifically, the paper is divided into two parts: first, it discusses the personalized learning recommendation problem based on lightweight GNNs, analyzing the limitations and challenges of existing research; second, it designs a personalized learning recommendation model based on lightweight GNNs and proposes corresponding optimization strategies. This study aims to provide a new solution for personalized learning in higher education, advancing the application and development of educational technology.

KEYWORDS

mobile education technology, personalized learning, graph neural networks (GNNs), lightweight, recommendation systems, higher education

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1 INTRODUCTION

With the rapid development of information technology, mobile education technology has been widely applied globally, especially in higher education. The widespread use of mobile devices and the continuous improvement of network environments have made learning no longer limited to traditional classroom teaching but have entered a more flexible and personalized learning era [1–4]. Personalized learning, as a student-centered educational model, aims to provide customized learning content and methods based on each student's interests, needs, and learning progress. The construction of school characteristics and professional features is key for universities to adopt differentiated development paths and enhance core competitiveness. Therefore, the realization of personalized learning in higher education is an important aspect of strengthening the construction of professional and institutional characteristics. As an important tool to promote personalized learning, mobile education technology is gradually changing teaching and learning methods in higher education [5–8]. However, how to fully utilize mobile education technology, especially how to accurately recommend the most suitable learning resources to each student, remains an important research topic in the field of personalized learning in higher education.

Although studies have explored the application of mobile education technology in personalized learning in recent years, most research has not delved into how advanced technologies, particularly graph neural networks (GNNs), can precisely realize efficient learning recommendation systems [9–11]. Research on personalized learning recommendation systems is of great significance for improving student learning outcomes, enhancing the utilization of educational resources, and optimizing educational services. This research not only provides new ideas for teaching reform in higher education but also offers valuable theoretical support for the development and application of subsequent educational technologies [12–16]. By constructing personalized recommendation models based on GNN, we can deeply mine students' learning behaviors, better meet their personalized learning needs, and promote the improvement of educational equity and quality.

However, existing research methods for personalized learning recommendations generally have certain limitations. Many studies rely on traditional recommendation algorithms and fail to fully consider the relationships and interactions among learners, leading to lower accuracy and flexibility in the recommendation results [17–19]. Current recommendation models typically overlook the nonlinear relationships and complex dependencies that emerge in students' learning processes. Furthermore, many recommendation systems fail to effectively integrate multidimensional student information, such as learning progress and changes in interests, which results in recommendations that do not precisely match students' needs. To overcome these shortcomings, recommendation systems based on lightweight GNN provide new possibilities for improving the precision of personalized recommendations.

This paper mainly focuses on how to apply lightweight GNN technology to promote the development of personalized learning recommendation systems in higher education. The first part will provide a detailed description of the personalized learning recommendation problem based on lightweight GNN, analyzing the advantages and challenges of this technology in personalized recommendations. The second part will explore the design of personalized learning recommendation models based

on this technology, with a focus on model architecture and optimization strategies. Through this research, we aim not only to improve the accuracy and efficiency of personalized learning recommendation systems but also to provide practical solutions for intelligent teaching in the higher education field. The innovation and practical significance of this study, especially in enhancing learning outcomes and promoting the development of educational technology, have important academic value and application prospects.

2 PERSONALIZED LEARNING RECOMMENDATION MODEL FOR HIGHER EDUCATION BASED ON MOBILE INTERACTION

2.1 Problem description

Personalized learning recommendations in higher education face complex learning needs and behavior patterns among students. Traditional recommendation systems often rely on content-based recommendations or collaborative filtering (CF) algorithms, but these methods fail to effectively capture the nonlinear relationships and interaction features in students' learning behaviors. Moreover, in the mobile learning environment, the system needs to process large amounts of student data in real time and provide quick responses. However, traditional GNNs generally have high computational complexity and long inference times, making it difficult to meet the efficiency requirements of practical applications. Therefore, this paper focuses on the research of personalized learning recommendation models for higher education based on lightweight GNN. GNNs have strong graph-structure modeling capabilities, enabling the establishment of complex relationships between multidimensional data during the student's learning process. The lightweight design can reduce the model's energy consumption and ensure the system responds promptly to students' learning progress, interest changes, and interactions with other students, thus providing smooth and timely learning resource recommendations on mobile platforms.

In a mobile education environment, students' learning behaviors are not limited to the classroom but are extensively interacted with through various mobile devices and platforms. These interactions include browsing learning resources, participating in online discussions, submitting assignments, receiving quiz feedback, and more. These interactions can be modeled using a mobile interaction graph. In the mobile interaction graph, nodes can represent students, learning items, or learning support information. The edges in the graph represent the relationships between nodes, which can be defined based on factors such as the co-occurrence of students' learning histories, the relevance of learning resources, or the frequency of interactions between students and learning resources. Thus, GNNs can propagate information across this graph structure to mine the potential relationships between students and learning resources. Suppose the embedding vector of student i is denoted as a_i , the neighboring node u is denoted as a_u , and the attention score of student i towards learning resource u , generated by the attention mechanism, is denoted as $\beta_{i,u}$. The training matrix is denoted as q , and the bias vector is denoted as y . The most commonly used methods are given by formulas (1) and (2), and formula (3) is the aggregation function:

$$AV : i = \frac{1}{|V_i|} \sum_{u \in V_i} a_u \quad (1)$$

$$ATT : \beta_{i,u} = \text{softmax}_u \left(q^s [a_i, a_u] + y \right) \quad (2)$$

$$i = \sum_{u \in V_i} \beta_{i,u} a_u \quad (3)$$

In traditional GNN models, many methods aggregate the neighborhood information of students and learning resources into two nodes and an edge when learning the mobile interactions between students and learning resources, thus compressing the local structure. Although this approach simplifies the computation to some extent, it may limit the exploration of local structures, resulting in the model's inability to effectively distinguish useful patterns from noise. For example, in large-scale higher education environments, interactions and behaviors between students and learning resources are diverse and complex. Traditional weighted aggregation methods may not capture these details, resulting in a reduced level of personalization and accuracy in the recommendation results. At the same time, existing models, such as BiGNN and DuaIGAT, although able to effectively utilize the mobile interaction relationships between students and learning resources, tend to have high computational complexity in GNNs, especially when handling large-scale graph data. They often require long training and inference times, affecting the real-time response ability of the model. This severely impacts the performance of personalized learning recommendation systems under mobile education technology because mobile devices often have limited computational resources and storage capacity. The system needs to ensure accurate recommendations while providing low-latency responses.

The lightweight neighborhood-enhanced recommendation model proposed in this paper provides a solution with computational and recommendation precision advantages for the specific problems in personalized learning recommendation systems in higher education. The lightweight design allows the model to efficiently handle large-scale student data and relationships with learning resources, supporting real-time learning progress tracking and dynamic recommendations. In practical applications, students' learning interests and needs change constantly, and the recommendation system needs to respond quickly and adjust the recommended content based on students' behavior. The lightweight model reduces the complexity of computational steps, enabling fast learning behavior analysis and personalized recommendations under limited hardware resources, making it particularly suitable for online education platforms that require personalized recommendations for large student populations.

Regarding the selection of neighboring nodes, the model design considers how to effectively select and utilize the most relevant neighboring nodes, avoiding excessive reliance on noisy information. Unlike traditional models, which are often disturbed by irrelevant nodes when selecting neighboring nodes, the model optimizes the neighbor selection strategy to effectively reduce overemphasis on noisy data, focusing on nodes related to students' learning interests and needs. This further improves the recommendation quality and personalization level. This optimization strategy enables the model to not only enhance the recommendation effectiveness when learning the complex interactions between students and learning resources but also significantly improve the model's robustness, avoiding performance fluctuations in large-scale graph data.

2.2 Model design

The lightweight neighborhood mobile interaction enhanced recommendation model proposed in this paper consists of four key modules:

1. **Graph embedding module:** The graph embedding module is responsible for converting the multidimensional interaction information between students and learning resources into low-dimensional vector representations. Based on the idea of GNN, the relationships between students and learning resources are constructed as a graph structure. The graph embedding module learns from this graph data and maps each node to a low-dimensional embedding vector. These embedding vectors not only retain historical interaction information between students and learning resources but also capture students' interest changes and learning needs, providing a foundation for the subsequent recommendation process. The core of this module lies in the efficient transmission of information through the propagation mechanism of GNNs, thereby mining potential patterns and relationships within the graph structure.
2. **Neighbor mobile interaction module:** This module specifically handles the neighborhood interaction information between students and learning resources. Unlike traditional methods that aggregate all neighbor information into a single node, the neighbor mobile interaction module dynamically selects neighboring nodes that are highly relevant to the current node, conducting personalized information propagation and interaction. The design of this module is inspired by the frequent interactions between students and specific learning resources or other students during mobile learning, which reflect students' learning preferences and needs. The goal of this module is to optimize the precision of the recommendation results by considering the close interactions between students and related learning resources. For example, during the learning process, certain learning resources may be used frequently or highly correlated with the student's learning behavior. This module can precisely capture such relationships and further improve the personalization of the recommendations.
3. **Lightweight neighbor sampling aggregation module:** The lightweight neighbor sampling aggregation module is one of the core innovations of the model. This module addresses the computational bottlenecks that arise when traditional GNNs handle large-scale graph data. Traditional GNNs require the aggregation of a large amount of neighbor information, which causes a sharp increase in computational complexity in large-scale graph data. The model introduces neighbor sampling techniques to effectively reduce the number of neighboring nodes that need to be processed while still maintaining sufficient information expressiveness. In this module, the model selects the most representative and relevant neighboring nodes for information aggregation based on a pre-defined sampling strategy, avoiding the processing of a large number of irrelevant nodes and greatly improving computational efficiency.
4. **Prediction module:** The prediction module is responsible for converting the embedding information learned from the previous three modules into specific personalized learning recommendations. This module interacts with the embedding vectors of students and learning resources to calculate the learning resources that students are likely to be interested in and ranks them according

to the recommendation algorithm. The optimization goal of this module is to improve the accuracy and personalization of the recommendations as much as possible, ensuring that each student receives recommendations that align with their learning interests and needs.

Figure 1 shows the proposed model architecture.

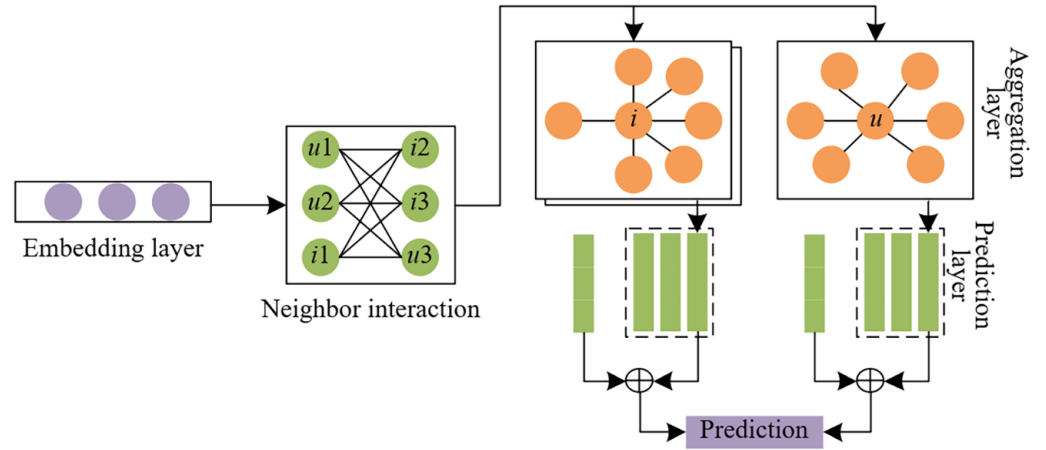


Fig. 1. Architecture of personalized learning recommendation model in higher education

Neighbor-neighbor mobile interaction. In personalized learning recommendations in higher education, effectively modeling the interaction relationships between students and learning resources, especially mobile interactions between students, is key to improving recommendation accuracy and personalization. The construction of neighborhood mobile interactions focuses on students' interactions with other students and learning resources in the mobile environment, providing more granular and dynamic learning information for the recommendation system. Generally, for predicting values, there are two types of weights: average weight and attention weight.

$$AV : \hat{b}_{i,n} = \left\langle \frac{1}{|V_i|} \sum_{u \in V_i} a_u, \frac{1}{|V_n|} \sum_{u \in V_n} a_k \right\rangle = \sum_{u \in V_i} \sum_{k \in V_n} \frac{1}{|V_i||V_n|} \langle a_u, a_k \rangle \quad (4)$$

$$ATT : \hat{b}_{i,n} = \left\langle \sum_{u \in V_i} \beta_{i,u} a_u, \sum_{k \in V_n} \beta_{n,k} a_k \right\rangle = \sum_{u \in V_i, k \in V_n} \beta_{i,u} \beta_{n,k} \langle a_u, a_k \rangle \quad (5)$$

The construction of neighborhood mobile interactions is based on students' behavior data from mobile devices in higher education. This data includes, but is not limited to, student browsing records of learning content, discussion interactions, assignment submissions, real-time feedback, and others. In traditional graph-based models, the interactions between students and learning resources are typically modeled through a graph structure, where students are nodes, learning resources are another type of node, and interactions between students and learning resources form edges. However, in the mobile education environment, students' learning behaviors are becoming more personalized, dynamic, and constantly changing. Therefore, traditional GNN methods cannot fully capture these subtle interaction differences, especially when considering higher-order neighborhood information, which may confuse noise with valid patterns, thus affecting the accuracy of the recommendation. To address this issue, the dual-attention network proposed in this paper introduces an attention mechanism to improve the weighted aggregation of

neighborhood information. Suppose that the student node is represented by a_p , the neighboring student node is represented by a_u , the learning resource node is represented by a_i , the neighboring learning resource node is represented by a_k , the bias term is represented by y , and the training parameter matrix is represented by q . The weight value between student and learning resource nodes is represented by $\beta_{u,k}$. The specific expressions are given as:

$$\beta_{u,k} = \text{softmax}_{u,k} \left(q^S [a_i, a_u, a_n, a_k] + y \right) \quad (6)$$

$$\hat{b}_{i,n} = \sum_{u \in V_i} \sum_{k \in V_n} \beta_{u,k} \langle a_u, a_k \rangle \quad (7)$$

In the higher education scenario, students' learning needs, learning styles, and interaction modes are highly personalized. The dual-attention network, through a refined weighting mechanism, can better explore dynamic interaction relationships between students on mobile devices. Specifically, the dual-attention network enhances the modeling ability of neighborhood mobile interactions in two ways:

1. **Local attention mechanism:** In mobile education recommendations, each student's learning behavior is closely linked to other students and learning resources in their neighborhood. These students may collaborate in the same study group or engage in similar learning activities at different times. The local attention mechanism assigns appropriate weights to different neighboring nodes, enabling the model to capture the fine-grained interaction relationships between students in the mobile environment. For example, during a certain period, student A might gain important knowledge about course content through a discussion with student B. This interaction should be assigned a higher weight in the recommendation process. The local attention mechanism dynamically calculates the influence of neighboring nodes to weight the interactions between students, ensuring the model can better identify which learning behaviors have a greater impact on students' interests and needs.
2. **Global attention mechanism:** Unlike the local attention mechanism, the global attention mechanism considers the position and relationships of students within the entire learning graph. By focusing on the global information of all nodes in the entire educational environment, the model can recognize long-term interaction patterns between different students. Especially in large-scale higher education environments, interactions between students may present high heterogeneity. Some students' behaviors may reflect global learning trends or patterns. For example, some students may show strong interest and frequent interactions with multiple learning resources, and these students' behaviors may provide strong guidance for learning resource recommendations. The global attention mechanism, by modeling the global structure of students and learning resources, can better reveal and leverage this global information, thereby improving the accuracy and personalization of the recommendation system.

Lightweight neighbor aggregation. In personalized learning recommendations in higher education based on mobile interaction technology, the principle of lightweight neighborhood mobile interaction aggregation primarily aims to reduce computational complexity, improve recommendation efficiency, and ensure the extraction of meaningful feature representations from mobile interactions between students and learning resources. This design not only responds to the demand for real-time recommendations in large-scale educational environments but also enhances the model's scalability and practicality by simplifying the traditional architecture

of graph convolutional networks (GCNs), making it especially suitable for scenarios where efficient inference is required on resource-constrained mobile devices.

The core of the lightweight design is to remove the complex network components in traditional GCNs, such as weight matrices and activation functions, retaining only the most basic graph linear propagation operations. In the context of personalized learning recommendations in higher education, the interaction data between students and learning resources itself contains a wealth of useful information, reflecting students' learning interests and behavior patterns. Therefore, the model does not need to rely on additional attribute information about students or learning resources but focuses on learning the relationships between students and learning resources via the graph propagation mechanism. This simplified design reduces the number of model parameters, decreases complexity, and enables more efficient operation, especially when making personalized recommendations for large numbers of students on mobile devices.

The key to this lightweight design is the graph propagation aggregation operation. In traditional GCNs, the node embedding vectors are updated by weighted propagation with neighboring nodes. Each layer of graph convolution requires matrix multiplication, activation function calculations, and other operations, which incur significant computational and storage overhead in large-scale datasets and deep network structures. In the lightweight neighborhood mobile interaction model, we simplify the process to a weighted averaging operation for updating node features. This means that in each layer of graph propagation, the feature vector of a student node is updated based on the features of its neighboring nodes through weighted averaging.

Furthermore, this paper also explores the lightweight aggregation approach in the multi-layer design of the model. In each layer of graph propagation, feature updates are performed via weighted averaging with neighboring nodes. The embedding vector of a student node gradually incorporates more information about learning resources in its neighborhood. As the number of graph propagation layers increases, the model is able to progressively capture more complex interaction relationships between students and learning resources, leading to more accurate personalized recommendations. For example, student A may interact with only certain learning resources at a specific moment, but through multi-layer propagation, the system can effectively capture the underlying learning needs and interest changes behind these interactions and recommend more relevant learning resources. Specifically, suppose the feature vector or initial embedding of node k is represented by a_k , the outputs of the first and second graph propagation layers are represented by a_u^1 and a_u^2 , and the neighbor sets of nodes u and i are represented by V_u and V_i . This paper calculates the high-order neighbor nodes in GCN based on stacked graph propagation layers.

$$a_u^2 = \left(\frac{1}{|V_u|} \sum_{u \in V_u} a_k \right) \quad (8)$$

$$a_i^2 = \left(\frac{1}{|V_i|} \sum_{u \in V_i} a_u^1 \right) \quad (9)$$

The lightweight neighborhood mobile interaction aggregation design not only optimizes the computational efficiency of the model but also ensures the accuracy of personalized recommendations. Through multi-level feature aggregation, the model can gradually enhance its perception of students' interest changes, ensuring that the recommendation results are more aligned with the students' learning needs

and behavioral characteristics. For example, certain mobile interactions during the learning process, such as frequent clicks and rating behaviors by students, can be effectively captured and utilized by the model through the graph propagation mechanism, thus improving the personalization and accuracy of recommendations.

Training method. The core principle of the training method for the constructed lightweight personalized learning recommendation model in higher education lies in effectively capturing the dynamic interaction relationships between students and learning resources through graph propagation operations and optimizing the model's performance using the cross-entropy loss function. The goal of the model is to learn students' interests and behavior patterns from their mobile interaction data and then recommend the most relevant learning resources. During training, the cross-entropy loss function is used to measure the gap between the model's predictions and the actual labels. For each student, the model generates a predicted probability based on their interactions with learning resources. This probability reflects the student's level of interest in a particular learning resource. The loss function compares the predicted probability with the actual 0 or 1 label, calculating the loss value. If there is a large discrepancy between the model's predicted result and the actual label, the cross-entropy loss function penalizes this discrepancy, thereby encouraging the model to gradually adjust its parameters during training to reduce prediction errors. Suppose the regularization term controlling overfitting is represented by $\eta \|\phi\|_2^2$, and the predicted value is represented by $\hat{b}_{i,n}$, the specific loss function is:

$$LOSS(B, \hat{B}) = -\sum_{b_{i,n}=1} \log(\hat{b}_{i,n}) - \sum_{b_{i,n}=0} \log(1 - \hat{b}_{i,n}) + \eta \|\phi\|_2^2 \quad (10)$$

In the context of personalized learning recommendations in higher education, the training process of the GNN relies on the interaction graph between students and learning resources. At each layer, node features are updated through weighted averaging during graph propagation. In this process, the features of student nodes are updated based on their interaction information with surrounding learning resource nodes. After multiple layers of propagation, a node representation rich in learning behavior information is obtained. During training, the cross-entropy loss function is used to optimize the predicted results for each student node, ensuring that the final output of learning resource recommendations aligns as closely as possible with the student's interests. Due to the lightweight design, the model reduces computational complexity while still effectively extracting meaningful features from large amounts of mobile interaction data. As a result, the model's weight update speed is faster during training, enabling efficient personalized recommendations under large-scale student data. Figure 2 illustrates the learning training process of the model presented in this paper.

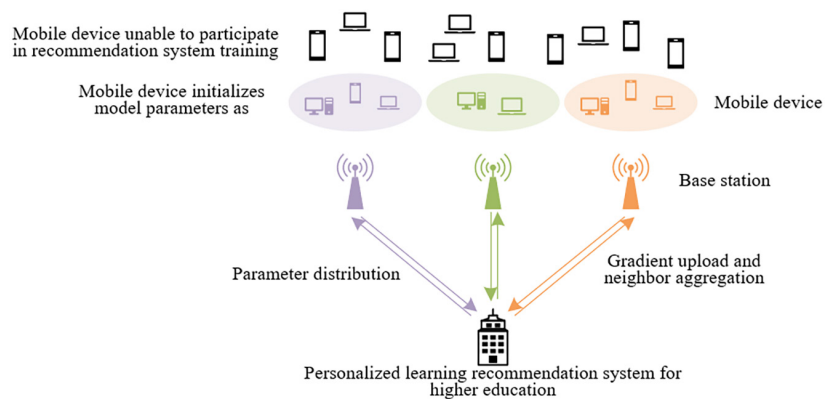


Fig. 2. Learning training process of the proposed model

3 EXPERIMENTAL RESULTS AND ANALYSIS

Based on the experimental results shown in Table 1, we can observe the performance of various recommendation models across multiple datasets. Overall, neighborhood-based CF performs well across the four datasets, especially on the EdX MOOC Dataset and Khan Academy Learning Paths Dataset, where the area under the curve (AUC) values are 0.7213 and 0.8326, respectively, and the accuracy (ACC) values are 0.6125 and 0.7562, demonstrating high prediction capability and stability. Compared to traditional singular value decomposition (SVD), SVD performs more consistently but slightly underperforms on certain datasets, especially with lower AUC and ACC values, and cannot compete with neighborhood-based CF methods. For deep learning-based recommendation models, deep factorization machines (DFMs) and autoencoder-based recommendations (AutoRec) show stronger results, particularly on the Khan Academy Learning Paths Dataset and Code.org Dataset. Their AUC and ACC values reach 0.8895 and 0.9451, as well as 0.9458 and 0.8895, respectively, surpassing traditional CF methods. Additionally, deep knowledge network (DKN) also performs excellently, especially on the Student Performance Dataset and Code.org Dataset, with AUC values of 0.9125 and 0.9452, and ACC values of 0.8352 and 0.8841, demonstrating its advantages in integrating deep learning with knowledge graphs. Finally, the model proposed in this paper achieves outstanding results across all datasets, particularly on the Code.org Dataset, where the AUC reaches 0.9652 and the ACC is 0.9125, showcasing its exceptional performance in personalized learning recommendations for higher education.

Table 1. Experimental results of different lightweight recommendation algorithms in personalized learning recommendation for higher education

Model	EdX MOOC Dataset		Student Performance Dataset		Khan Academy Learning Paths Dataset		Code.org Dataset	
	AUC	ACC	AUC	ACC	AUC	ACC	AUC	ACC
SVD	0.6785	0.6258	0.8895	0.8256	0.8256	0.7452	0.9325	0.8752
Neighborhood-based CF	0.7213	0.6125	0.9125	0.8124	0.8326	0.7562	0.9456	0.8762
FMR	0.6125	0.5785	0.7251	0.6785	0.7215	0.6895	0.8262	0.7213
DFM	0.7156	0.6623	0.9256	0.8262	0.8895	0.7894	0.9458	0.8723
GBDT	0.6658	0.6325	0.8895	0.8124	0.8326	0.7785	0.9466	0.8895
NCF	0.6451	0.6251	0.8758	0.8126	0.8325	0.7562	0.9326	0.8785
AutoRec	0.7215	0.6325	0.9235	0.8326	0.8541	0.7785	0.9451	0.8895
DKN	0.7128	0.6589	0.9125	0.8352	0.8895	0.7895	0.9452	0.8841
The proposed model	0.7452	0.6895	0.9236	0.9236	0.8926	0.8125	0.9652	0.9125

From the experimental results in Figure 3 on the training set, the proposed model demonstrates excellent performance across multiple Top-K recommendation tasks (Precision@K and Recall@K), especially in tasks with smaller K values such as Precision@1, 2, 5, and 10, where it significantly outperforms other traditional and deep learning models. For instance, at Precision@1, the proposed model achieves a precision of 0.06, which is the same as that of neighborhood-based CF but significantly

higher than SVD (0.018) and other models. In terms of Recall@K performance, the proposed model also shows strong recommendation capability, particularly at larger K values (e.g., 20, 50, 100). The recall value gradually increases, ultimately reaching 0.21 at Recall@100, far surpassing other models such as SVD (0.1) and AutoRec (0.13). This indicates that the proposed model has a balanced advantage in both the breadth and depth of recommendation results, providing high-quality personalized recommendations in different recommendation scenarios.

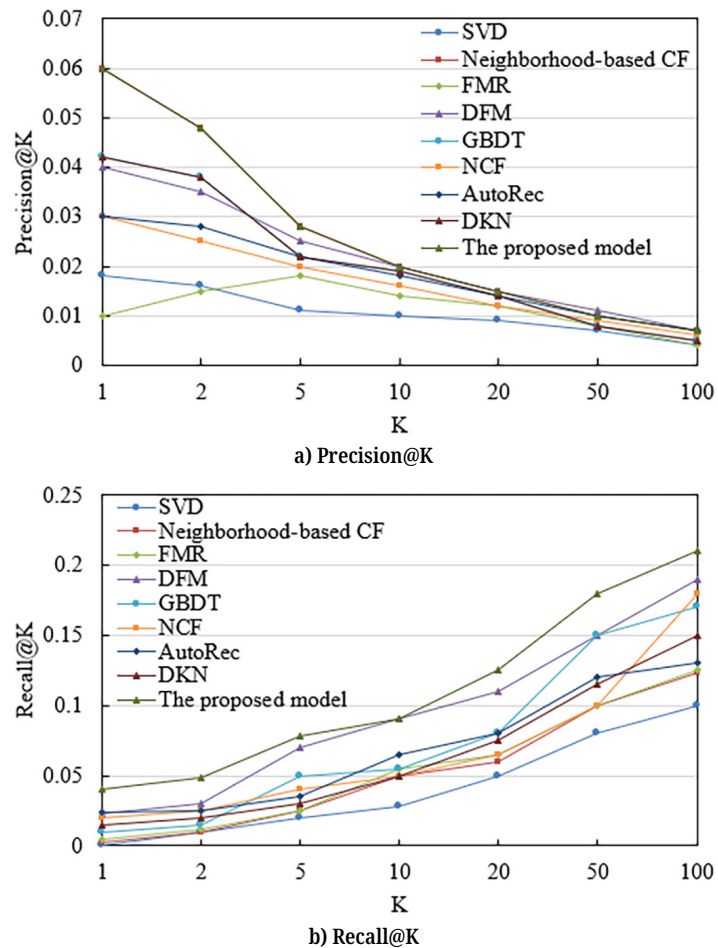


Fig. 3. Top-K recommendation results on the training set

From the experimental data provided in Figure 4 for the validation set, the proposed model demonstrates significant advantages across multiple Top-K recommendation tasks, particularly in balancing precision and recall. In the Precision@K metric, the proposed model outperforms all other models across all K values, especially at lower K values (e.g., 1, 2, 5), where its precision reaches 0.25, 0.24, and 0.19, respectively, significantly higher than other models. In comparison, AutoRec and NCF achieve a maximum precision of only 0.2 and 0.18, while traditional models such as SVD and Neighborhood-based CF perform noticeably worse at lower K values (0.14 and 0.12, respectively). For the Recall@K metric, the proposed model also shows outstanding performance across all K values (from 1 to 100), especially at higher K values (such as 50 and 100), where recall values reach 0.495 and 0.64, respectively. This performance is on par with models such as AutoRec and SVD, but superior to traditional models such as FMR, DFM, and DKN, demonstrating its advantage in coverage.

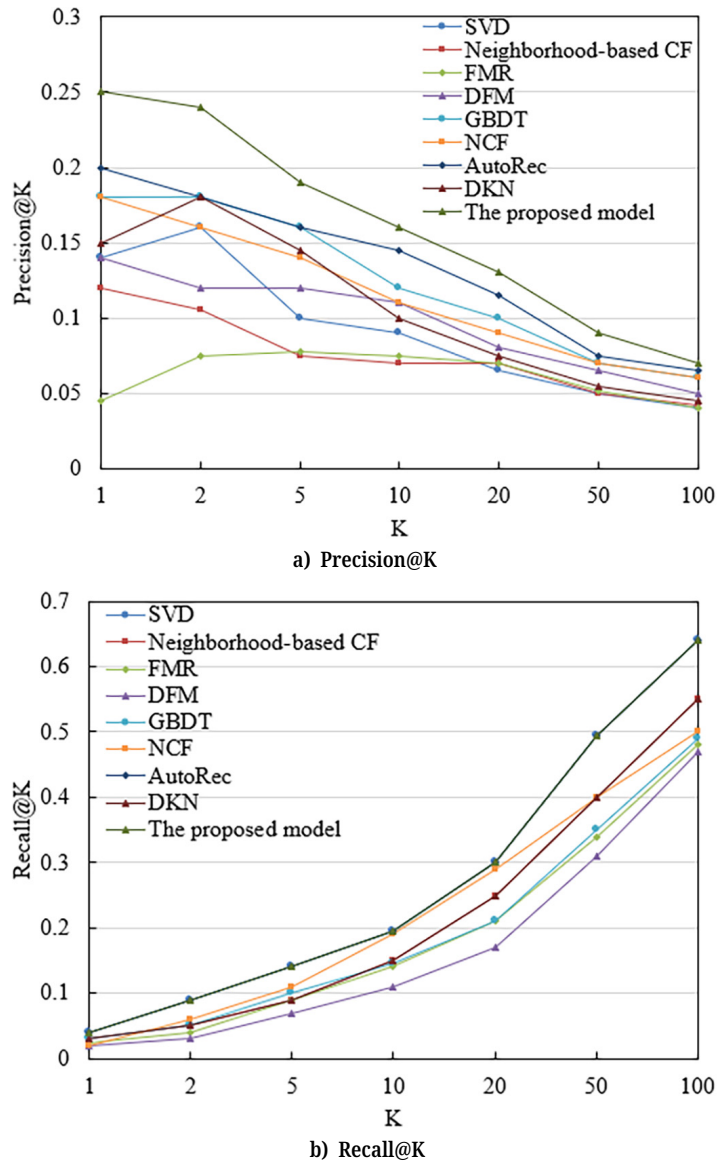


Fig. 4. Top-K recommendation results on the validation set

The ablation study in Table 2 compares the performance of different model variants across multiple datasets. The results show that the model using only first-order attention networks yields relatively lower AUC values across all datasets, with 0.7452 for the EdX MOOC Dataset, 0.9125 for the Student Performance Dataset, 0.8895 for the Khan Academy Learning Paths Dataset, and 0.9562 for the Code.org Dataset. In comparison, the model without neighbor interaction performs better on most datasets, particularly on the Student Performance Dataset (AUC = 0.9263) and Khan Academy Learning Paths Dataset (AUC = 0.8795), showing better recommendation performance, but still lags behind the complete proposed model. Finally, the complete proposed model achieves the highest AUC values across all datasets, especially on the Code.org Dataset, where the AUC reaches 0.9826, showing a significant improvement. The AUC values for other datasets are 0.7532 (EdX MOOC Dataset), 0.9356 (Student Performance Dataset), and 0.9195 (Khan Academy Learning Paths Dataset). These results demonstrate that combining neighbor interaction and a more complex GNN architecture can significantly improve the model’s recommendation performance.

Table 2. Ablation study

Model	EdX MOOC Dataset	Student Performance Dataset	Khan Academy Learning Paths Dataset	Code.org Dataset
	AUC	AUC	AUC	AUC
Only First-Order Attention Network	0.7452	0.9125	0.8895	0.9562
No Neighbor Interaction	0.7362	0.9263	0.8795	0.9451
Complete Model (Proposed)	0.7532	0.9356	0.9195	0.9826

4 CONCLUSION

This study delves into how leveraging lightweight GNN techniques can drive the development of personalized learning recommendation systems in higher education. In the research section, we first provided a detailed discussion on the importance and challenges of personalized learning recommendation systems in higher education, analyzing the limitations of traditional recommendation methods when dealing with complex user behaviors and multidimensional learning needs. Based on this, we proposed a recommendation model based on lightweight GNN, with a focus on model architecture and optimization strategies, and experimentally verified the model's recommendation performance across different datasets. The results show that the lightweight GNN-based model outperforms traditional methods on multiple evaluation metrics. Through ablation experiments on different training strategies and epoch learning frequencies, it was found that the model's precision and recall were optimized on both the training and validation sets, especially on complex learning path data, where the model better captures nonlinear relationships and potential interactions between users and learning resources.

By innovatively applying lightweight GNN techniques, this study addresses the challenges encountered in personalized learning recommendations in higher education. Compared to traditional CF and matrix factorization methods, GNN can effectively model the complex nonlinear relationships between users and learning content, and improve recommendation accuracy and coverage through the neighbor interaction mechanism. This research provides a new technical pathway for personalized learning recommendation systems, offering more accurate and diverse learning resource recommendations for students in higher education. The findings have significant academic value and practical implications.

5 ACKNOWLEDGEMENT

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