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PAPER

Teaching Strategies and Implementation Paths for Interactive Mobile Learning Platforms in Higher Education

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ABSTRACT

Against the backdrop of widespread information technology and mobile devices, the digital transformation of higher education is advancing rapidly, and interactive mobile learning platforms have become key tools for overcoming the time-space limitations of traditional teaching and meeting students' personalized learning needs. However, existing platforms still face practical challenges in areas such as teaching strategy formulation, implementation path optimization, and technological adaptability, limiting their educational value. Although current research addresses the development and application of mobile learning platforms, there are significant limitations. Some studies focus on technological architecture design but fail to deeply integrate teaching strategies with technology applications. Learning resource recommendations largely rely on historical user data, neglecting real-time learning states and interactive intentions. Furthermore, the application of collaborative filtering algorithms has not effectively incorporated graph neural networks with mobile interaction scenarios, resulting in insufficient recommendation accuracy and scenario adaptability. This paper focuses on two key areas: first, exploring the teaching application of interactive mobile learning platforms based on learning resource recommendations by analyzing the intersections between resource recommendation and teaching processes and developing personalized teaching strategies tailored to higher education scenarios; second, developing a collaborative filtering algorithm that integrates mobile interaction intentions with graph neural networks, incorporating real-time student interaction data into the algorithm model to enhance the accuracy of learning preference prediction and resource recommendations.

KEYWORDS

interactive mobile learning platform, teaching strategies, learning resource recommendations, graph neural networks, collaborative filtering algorithm

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1 INTRODUCTION

With the rapid development of information technology and the widespread use of mobile smart devices, the teaching model in higher education is undergoing profound changes [1–4]. The traditional higher education model [5, 6] is gradually showing limitations in terms of time-space constraints, personalized teaching, and teacher-student interaction. In contrast, interactive mobile learning platforms [7, 8], with their convenience, immediacy, and interactivity, have become an important tool to address the shortcomings of traditional teaching and promote the digital transformation of higher education. Currently, students' learning needs are becoming increasingly diversified and personalized [9, 10]. They are no longer satisfied with passively receiving knowledge but are more eager to engage in real-time interaction, self-exploration, and personalized learning during the learning process. Interactive mobile learning platforms can break the time-space barriers of classroom teaching, providing students with rich learning resources and various interactive channels. However, in practice, how to formulate effective teaching strategies and optimize implementation paths to fully utilize their advantages remains a problem that needs to be addressed in the field of higher education.

Existing research on mobile learning platforms has achieved some results but still has some defects and limitations in terms of research methods. Some studies focus on the technical development and functionality of the platform, such as references [11–14], which mainly focus on the architecture design of mobile learning platforms, with insufficient attention to the integration of teaching strategies and technology applications and failing to fully consider the practical needs in the teaching process. Studies in reference [15] involve learning resource recommendations but use relatively simple recommendation methods, mainly based on users' historical browsing records, neglecting learners' real-time learning status and interaction intentions, resulting in low recommendation accuracy. Studies in references [16, 17] on the application of collaborative filtering algorithms do not effectively integrate graph neural networks with mobile interaction intentions, making the algorithm's performance insufficient when handling user preference prediction in complex learning scenarios. The limitations of these research methods make it difficult for existing results to effectively guide the efficient application of interactive mobile learning platforms in higher education.

This paper mainly focuses on two core areas. The first is the research on the implementation of a collaborative filtering algorithm that integrates mobile interaction intentions with graph neural networks. This part will aim to address the deficiencies of existing algorithms in the application of learning platforms by incorporating students' mobile interaction intentions into the graph neural network collaborative filtering algorithm, enhancing the algorithm's ability to predict students' learning preferences and providing stronger technical support for learning resource recommendation and personalized teaching. The second is the research on the teaching application of interactive mobile learning platforms in higher education based on learning resource recommendations. This part will deeply analyze the intersection between learning resource recommendations and teaching applications, exploring how to accurately push suitable learning resources to students based on their learning characteristics, knowledge mastery levels, and other factors, and develop corresponding teaching strategies to improve the targeted and effective nature of teaching.

2 IMPLEMENTATION OF THE COLLABORATIVE FILTERING ALGORITHM INTEGRATED WITH MOBILE INTERACTION INTENTIONS AND GRAPH NEURAL NETWORKS

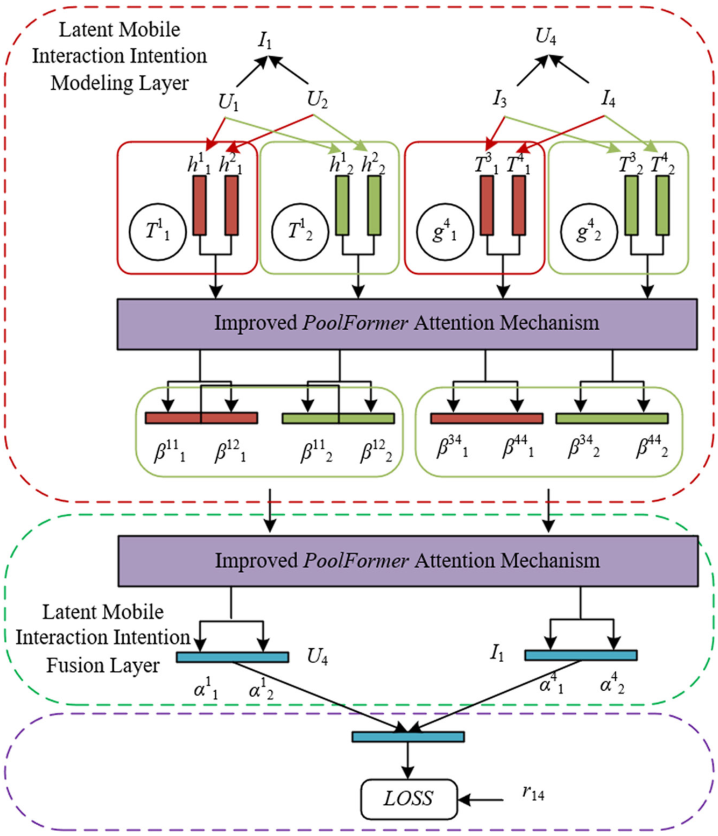

Fig. 1. Algorithm framework

The collaborative filtering algorithm integrated with mobile interaction intentions and graph neural networks is based on real learning scenarios of interactive mobile learning platforms. Through a three-layer progressive design, it achieves the accurate capture and prediction of user learning preferences: The latent intention modeling layer, as the structural foundation, first constructs a "user-learning resource-interaction behavior" heterogeneous graph from the initial mobile interaction intention data collected by the platform, using graph convolution networks to model the nodes and edges in the graph at a fine-grained level. Meanwhile, an improved PoolFormer attention mechanism is introduced, which assigns learnable attention weights to different neighborhood nodes during the message propagation process in the graph, thereby quantifying the differences in user preferences for different learning resources under the same interaction intention. The latent intention fusion layer receives the output from the modeling layer. For heterogeneous interaction intentions generated by users in different learning stages on the platform, dynamic fusion is performed again using the improved PoolFormer attention mechanism. The algorithm automatically identifies the correlation between different intentions and assigns fusion weights, ultimately generating user embedding vectors containing comprehensive learning preferences and learning resource embedding vectors containing resource adaptation scenarios. The rating prediction layer, as the output section, concatenates the final user and learning resource embedding vectors and inputs them into a multilayer perceptron adapted to mobile learning scenarios, outputting the user's interest score for a specific learning resource, providing the core decision-making basis for the platform's personalized resource recommendation, and realizing the complete transformation from interaction data to interest prediction. The specific algorithm framework is shown in Figure 1.

2.1 Improved PoolFormer attention mechanism

The improved PoolFormer attention mechanism used in this study focuses on adapting to the collaborative filtering needs of interactive mobile learning platforms. Based on retaining the core functionality of the token mixer module in the original PoolFormer, it is optimized for efficiently modeling mobile interaction intentions. The basic principle is first reflected in the adaptability design of computational efficiency. It follows the feature mixing logic of the token mixer module but simplifies redundant computational steps. While effectively extracting mobile interaction features such as user clicks, dwell time, and discussions, it reduces the model's computational load when processing real-time interaction data, meeting the platform's requirement for recommendation response speed. Secondly, a non-parametric spatial average pooling layer is used to implement cross-feature correlation modeling. This layer can automatically aggregate similar interaction patterns between users and the correlations between learning resources, effectively merging different types of mobile interaction features such as clicks, favorites, and notes, thus solving the problem of user-resource interaction data sparsity in mobile learning scenarios. Moreover, a residual network is embedded to construct a "shortcut" for feature propagation, retaining differentiated information of the original interaction features during multi-layer feature extraction. For example, it prevents the over-smoothing of differentiated questioning intentions from different students on the same knowledge point, thereby maintaining the model's ability to distinguish personalized interaction intentions. Ultimately, this provides efficient and precise feature inputs for the graph neural network collaborative filtering algorithm.

2.2 Latent mobile interaction intention modeling layer

The core starting point of the latent intention modeling layer is the fine-grained dissection of user-learning resource interaction behaviors in interactive mobile learning platforms. In mobile learning scenarios, user interaction behaviors, such as video playback speed adjustments, exercise submissions, and discussion forum comments, often correspond to a variety of latent intentions. Therefore, the algorithm predefines L types of user-specific mobile interaction intentions $\{t_L^i\}_{l=1}^{L}$ for each user and matches L types of triggered intention features $\{g_l^u\}_{l=1}^{L}$ for each learning resource. This division precisely fits the fragmented and contextual characteristics of mobile learning. For example, for "online homework" resources, the triggering intention features could correspond to "immediate error correction" and "consolidation exercises," while for "teaching live playback" resources, the features could correspond to "key review" and "detail supplementation," providing a foundational framework for subsequent intention modeling that aligns with actual learning needs.

The node-level improved PoolFormer attention mechanism is the core tool for accurate intention inference in the latent intention modeling layer. In interactive mobile learning platforms, under the same mobile interaction intention, different users may have significantly different preferences for the same resource. The node-level improved PoolFormer attention mechanism captures these fine-grained differences and infers the extent to which learning resource information affects user preferences: On the one hand, its non-parametric spatial average pooling layer can associate similar interaction patterns between users and correlations between learning resources. On the other hand, the simplified token mixer module can quickly process real-time interaction data generated on mobile devices while reducing computational complexity, ultimately generating weight coefficients that are more suitable for mobile learning scenarios, avoiding the biases of traditional attention mechanisms in sparse interaction data.

The latent intention modeling layer, through the combination of the improved PoolFormer attention unit and graph convolution networks, solves the efficiency bottleneck of traditional graph convolution aggregation. In mobile learning platforms, user interactions are highly real-time, and directly using graph convolution networks to aggregate the learning resource set from users' historical interactions would result in high time costs due to the need to traverse all neighboring nodes. Therefore, the algorithm embeds the improved PoolFormer attention unit, ATT_{NO}, in each graph convolution layer. This unit, based on the features of the user's current intention, dynamically calculates the actual interaction probability r_l^{iu} between user i and learning resource u under the l-th intention drive:

$$(r_l^{iu})^1 = ATT_{NO}\left((t_l^i)^1,(t_l^u)^1,l\right) \tag{1}$$

Assume that the user feature embedding is represented by $FE1$ and the learning resource feature embedding interacted with the user is represented by $FE2$, the specific expressions for the improved PoolFormer attention are:

$$h_1=\left[FE1 \,\|\, FE2_{RE}\right] \tag{2}$$

$$h_2 = \delta(Q_2 \cdot h_1 + y_2) \tag{3}$$

$$h_3 = POOLING(NORM(h_2)) + h_2 \tag{4}$$

$$(r_l^{iu})^1 = q^T \cdot h_3 \tag{5}$$

The latent intention modeling layer completes the recursive expression of user intentions through probability normalization and multi-order neighborhood aggregation. After obtaining the interaction probability r_l^{iu}, the algorithm normalizes the weight coefficient β_l^{iu} using the softmax function. This process effectively eliminates dimensional differences between different learning resources, ensuring that the first-order neighborhood intention $(t_l^i)^1$ output by the graph convolution layer accurately reflects the user's core preferences under a specific intention. Subsequently, the algorithm recursively aggregates the user intention into l-order neighborhood information through the iterative update of the graph convolution network, ultimately generating the user embedding vectors for L intentions $\{c_l^i\}_{l=1}^L$. Assuming that the activation function Leaky ReLU is represented by δ, the concatenation operation is represented by $\|$, and the node-level attention vector under the l-th interaction intention is represented by x_l^T, the expressions are:

$$(\beta_l^{iu})^1 = SOFTMAX(r_l^{in}) = \frac{\exp\left(\delta\left(x_l^T \cdot [(t_l^i)^1 \,\|\, (g_l^u)^1]\right)\right)}{\sum_{u\in U_i}\exp\left(\delta\left(x_l^T \cdot [(t_l^i)^1 \,\|\, (g_l^u)^1]\right)\right)} \tag{6}$$

$$(t_l^i)^1 = \delta\left((t_l^i)^1,(g_l^u)^1\right) \tag{7}$$

The information aggregated from the m–1-th order neighbors of user i and learning resource u based on the l-th interaction intention is represented by $(t_l^i)^{m-1}$ and $(g_l^u)^{m-1}$, with the layer aggregation function represented by $h(\cdot)$. The number of neighbors for learning resource u at the m–1-th order is represented by U_i. The recursive aggregation formula is as follows:

$$(t_l^i) = h\left((t_l^i)^{m-1}, \left\{(g_l^u)^{m-1} \mid u \in U_i\right\}\right) \tag{8}$$

2.3 Latent mobile interaction intention fusion layer

The core function of the latent intention fusion layer is to dynamically integrate the multi-dimensional intention features output by the latent intention modeling layer using an intention-level improved PoolFormer attention mechanism, achieving accurate aggregation of user learning preferences. In interactive mobile learning platforms, users' learning behaviors are often driven by multiple mobile interaction intentions simultaneously. For example, when a student watches a "Data Structures" course video, they may simultaneously have the intentions of "understanding basic concepts" and "strengthening problem-solving skills," and the contribution of each intention may vary throughout the learning stages. Therefore, the fusion layer takes L learning resource features $\{c_l^i\}_{l=1}^L$ of user i as input, and by associating the user's current overall learning state t_l^i with individual intention features c_l^i, it generates a unified feature embedding. An intention-level attention vector w is then introduced to calculate the importance score of the l-th intention, and finally, the normalized weight α_l^i is obtained using the Softmax function. This weight learning mechanism aligns with the dynamic nature of intentions in mobile learning and addresses differences in the volume of interaction data across different users through normalization, ensuring stable feature fusion results in both training and real-time recommendations, ultimately generating the final embedding c_i, which reflects the user's diverse intentions.

Specifically, assuming the intention-level improved PoolFormer attention mechanism is represented by ATT_{INT}, the weight of each learning resource feature is:

$$\alpha_1^i, \alpha_2^i, \ldots, \alpha_L^i = ATT_{INT}(c_1^i, c_2^i, \ldots, c_L^i) \tag{9}$$

Assuming the weight matrix is represented by Z_l and the bias vector is represented by y_l, the unified embedding process of learning c_l^i and t_l^i can be represented by the following equation:

$$f_l^i = \delta\left(Z_l \cdot [c_l^i \,\|\, t_l^i] + y_l\right) \tag{10}$$

Assuming the bias is represented by y, the importance of the l-th learning resource feature under the l-th interaction intention can be represented by:

$$\mu_l = \delta(w^S \cdot f_l^i + y) \tag{11}$$

The weight α_l^i of the l-th learning resource feature, obtained using the Softmax function, can be expressed by:

$$\alpha_l^i = \frac{\exp(\mu_v)}{\sum_{j=1}^{L}(\mu_j)} \tag{12}$$

The final embedding c_i for user i is:

$$c_i = \sum_{l=1}^{L} \alpha_l^i \cdot c_l^i \tag{13}$$

The latent intention fusion layer, through the symmetric embedding generation logic, simultaneously completes the intention aggregation of learning resources, providing bidirectional precise feature support for collaborative filtering. Consistent with the user embedding generation logic, the final embedding n_u of the learning resource does not solely depend on its own attributes but is aggregated through the mobile interaction intentions of all users who have interacted with the resource. For example, the embedding of the "Python Programming Practical" resource will integrate the intention features, such as "skill practice" and "project case reference," from all users who have accessed the resource and assign differentiated weights to the users' intentions using the intention-level improved PoolFormer attention mechanism. This bidirectional embedding design accurately adapts to the collaborative filtering needs of interactive mobile learning platforms. The user embedding c_u reflects "what the user needs," while the resource embedding n_u reflects "what the resource can offer," and their match directly determines the recommendation accuracy.

2.4 Rating prediction

The rating prediction of the graph neural network collaborative filtering algorithm that integrates mobile interaction intentions aims to accurately capture users' interest preferences for learning resources. The basic principle is to model the nonlinear association between the integrated mobile interaction intention user and learning resource embeddings using a multilayer perceptron (MLP). Specifically, the final embedding c_u of the user has aggregated multi-dimensional mobile interaction intentions from the interactive mobile learning platform, such as video playback speed adjustments, dwell time during exercise completion, and keywords in discussion forum questions. The final embedding n_u of the learning resource integrates various interaction features triggered by the resource, such as the difficulty of knowledge points, collaborative access relationships with other resources, and user annotations or feedback. By connecting these two embeddings as input to the MLP, the model can fully preserve the correlation information between the user's personalized learning needs and the resource features. The MLP, through multiple nonlinear transformations, captures the complex underlying associations between the user and the resource, ultimately outputting the predicted score for the user's interest in the learning resource. Assuming the concatenation function is represented by h_1, the weight matrix and bias term for the m-th layer are represented by Q_m and y_m, and the activation function is represented by δ, the prediction formulas are:

$$h_1 = [c_i \,\|\, n_u] \tag{14}$$

$$h_2 = \delta(Q_2 \cdot h_1 + y_2) \tag{15}$$

$$h_{m-1} = \delta(Q_m \cdot h_{m-1} + y_m) \tag{16}$$

$$e'_{i,u} = q^T \cdot h_3 \tag{17}$$

2.5 Loss function

The design of the algorithm's loss function focuses on accurately optimizing the rating prediction results and adapting to the characteristics of mobile learning scenarios. Its basic principle is to achieve a balance between prediction accuracy and model robustness through a combination of "base loss + regularization constraints." The base loss part focuses on minimizing the difference between predicted ratings and true ratings, using Mean Squared Error (MSE) as the core metric. When there is a discrepancy between the actual rating given by a user on the mobile platform for "probability theory exercises" and the predicted rating, MSE quantifies this deviation and drives model parameter optimization. Let P represent the predicted ratings set, and $e_{i,u}$ represent the true rating of user i for learning resource u. The base loss objective function can be expressed as:

$$LOSS_e = \frac{1}{2|P|} \sum_{(i,u \in P)} (e'_{i,u} - e_{i,u})^2 \tag{18}$$

Since interactive mobile learning platforms involve diverse user interaction intentions and some interaction data may be noisy, the model may become over-parameterized due to overfitting of multiple intention features or redundant interaction data. $L0$ regularization sparsifies the mobile interaction intention matrix and the categorical feature extraction matrices Q and N, automatically pruning the degrees of freedom that are irrelevant to the true ratings and retaining only those interaction intentions that have a significant impact on the ratings. Let φ represent the model parameters, and η represent the hyperparameter that balances rating loss and sparse regularization. The final objective function is:

$$\underset{\varphi}{MIN}\, LOSS = LOSS_e + \eta \|\varphi\|_0 \tag{19}$$

3 TEACHING APPLICATION OF INTERACTIVE MOBILE LEARNING PLATFORMS IN HIGHER EDUCATION BASED ON LEARNING RESOURCE RECOMMENDATION

The core application scenarios of the graph neural network collaborative filtering algorithm integrating mobile interaction intentions on interactive mobile learning platforms in higher education cover the entire process of pre-class preview, in-class interaction, and post-class consolidation. Before class, students' interaction data, such as dwell time when browsing the course syllabus and chapter click trajectories, are captured by the algorithm and converted into learning preference features. Combined with the graph neural network's modeling of the "student-knowledge point-resource" relationship, the algorithm accurately recommends preview videos and preparatory exercises that match the student's knowledge foundation. During class, when students send question keywords in the live discussion area or vote on the teacher's questions, the algorithm analyzes these real-time interaction intentions and dynamically adjusts the recommended content. The teaching strategy based on this algorithm should emphasize "dynamic adaptation" and "interaction enhancement": Teachers can rely on the platform to obtain real-time student interaction heatmaps, adjusting classroom teaching focuses accordingly. Simultaneously, an "interaction task-driven" mechanism is designed, where the algorithm optimizes resource recommendation logic based on labeled data, forming a closed loop of "student interaction – algorithm recommendation – teacher adjustment – student re-interaction." Figure 2 shows a schematic diagram of user-learning resource mobile interaction.

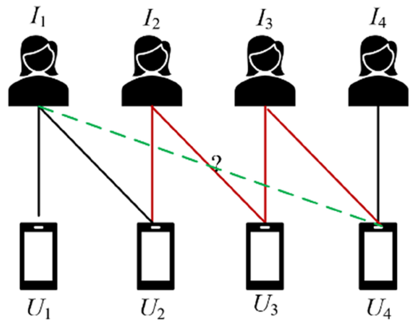

Fig. 2. User-learning resource mobile interaction schematic

The implementation path of the interactive mobile learning platform in higher education, using this recommendation algorithm, should proceed in phases: During the platform construction phase, multi-dimensional interaction data collection modules should be embedded, and the algorithm should be adapted to the platform's teaching functions, such as integrating the recommendation results interface with core modules like course pages, homework systems, and discussion areas, ensuring that recommended content naturally fits into the learning scenario. In the promotion phase, teacher and student training should be conducted simultaneously. Teachers are guided to interpret student interaction data through the platform's "algorithm feedback panel," while students are encouraged to use the platform's "personalized learning path" feature to track the learning progress of algorithm-recommended resources. In the effect optimization phase, a "dual-dimensional evaluation system" should be established, validating the technical effectiveness through the recommendation accuracy output by the algorithm and evaluating the teaching value through score improvements for corresponding knowledge points in the final exam and changes in student classroom interaction participation rate. Based on the evaluation results, the algorithm parameters and platform interaction design should be iterated, ultimately forming a complete implementation loop of "data collection – algorithm recommendation – teaching application – effect feedback – iterative optimization."

4 EXPERIMENTAL RESULTS AND ANALYSIS

Tables 1–3 systematically reveal the parameter tuning effects on the improvement of learning preference prediction accuracy from three key dimensions: model regularization, feature representation ability, and training process optimization. In Table 1, different datasets show a non-monotonic optimization trend: the Coursera dataset achieves RMSE = 0.3745 and MAE = 0.1458 when Drop Rate = 0.4, and RMSE further decreases to 0.3742 with MAE dropping to 0.1239 when Drop Rate = 0.2, demonstrating that appropriately lowering Drop Rate can enhance the model's ability to capture mobile interaction intentions. For the edX dataset, as Drop Rate decreases from 0.5 to 0.2, RMSE decreases from 0.9263 to 0.8826, and MAE decreases from 0.6854 to 0.6523, confirming that regularization improves the generalization ability of sparse mobile learning data. For the MOOC dataset, although MAE slightly increases at Drop Rate = 0.2, RMSE decreases from 0.9452 to 0.9356, still supporting that a reasonable Drop Rate optimizes model stability. In Table 2, 63-dimensional embedding performs best across all three datasets: RMSE = 0.3741 for Coursera, RMSE = 0.8759 for edX, and RMSE = 0.9254 for MOOC, indicating that 63 dimensions precisely balance the correlation expression between user mobile interaction intentions and resource features, avoiding information loss due to insufficient dimensions or overfitting due to excessive dimensions. In Table 3, batch size adaptation highlights the balance between training efficiency and accuracy: Coursera achieves RMSE = 0.3741 at batch size = 254, edX achieves RMSE = 0.8756 at batch size = 513, and MOOC achieves RMSE = 0.9236 at batch size = 513, showing that an appropriate batch size can accelerate model convergence and strengthen the prediction ability for student personalized learning preferences.

Table 1. Influence of drop rate on the algorithm

Drop Rate	Coursera		edX		MOOC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
0.5	0.3752	0.1625	0.9263	0.6854	0.9452	0.7325
0.4	0.3745	0.1458	0.8894	0.6789	0.9362	0.7456
0.3	0.3769	0.1236	0.8856	0.6623	0.9254	0.7258
0.2	0.3742	0.1259	0.8826	0.6523	0.9356	0.7369

Table 2. Influence of embedding dimensions on the algorithm

Embedding Dimension	Coursera		edX		MOOC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
31	0.3756	0.1326	0.8854	0.6623	0.9356	0.7325
63	0.3741	0.1256	0.8759	0.6678	0.9254	0.7258
127	0.3756	0.1268	0.8856	0.6523	0.9638	0.7369

Table 3. Influence of batch size on the algorithm

Batch Size	Coursera		edX		MOOC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
126	0.3785	0.1758	0.8869	0.6452	0.9456	0.7354
254	0.3741	0.1236	0.8845	0.6523	0.9258	0.7258
513	0.3769	0.1569	0.8756	0.6689	0.9236	0.7369

Table 4 visually demonstrates the significant advantage of the proposed algorithm in the recommendation task across three major educational datasets: Coursera, edX, and MOOC, through RMSE and MAE comparisons. In the Coursera dataset, the RMSE of the proposed algorithm is 0.3752, which is a 3.0% improvement over GraphSAGE's 0.3865, and the MAE is 0.1256, which is 23.9% lower than GraphSAGE's 0.1652. The proposed algorithm not only outperforms traditional matrix factorization algorithms like SVD and BiasSVD but also achieves a breakthrough in accuracy compared to graph neural network baselines. In the edX dataset, the proposed algorithm's RMSE is 0.8824, which is 3.3% lower than MMGCN's 0.9125, and the MAE is 0.6529, which is 4.7% lower than MMGCN's 0.6852, breaking the generalization bottleneck of graph models in large-scale educational data. In the MOOC dataset, the RMSE of 0.9235 is 1.4% lower than GraphSAGE's 0.9362, and the MAE of 0.7251 is 2.4% lower than GraphSAGE's 0.7426, confirming the algorithm's adaptability to domestic mobile learning scenarios. The source of performance improvement lies in the deep modeling of mobile interaction intentions: traditional algorithms rely solely on coarse-grained behaviors such as clicks and ratings, while the proposed algorithm captures mobile-specific interaction intentions, such as video playback speed, swipe trajectory, and question timing in discussion areas, coupling fine-grained intentions with the "user-resource" association network through a graph neural network, achieving an upgrade from "statistical association" to "intention-driven" learning preference prediction.

Table 4. Performance comparison of different algorithms on recommendation tasks across different datasets

Method	Coursera		edX		MOOC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
SVD	0.4123	0.2135	0.9235	0.7325	0.9562	0.7452
BiasSVD	0.3856	0.2145	0.9254	0.7256	0.9563	0.7589
Deep AutoRec	0.3745	0.4526	0.9215	0.7541	0.9653	0.7741
NADE-MF	0.3852	0.1756	0.9236	0.7258	0.9451	0.7452
GraphSAGE	0.3865	0.1652	0.9287	0.7235	0.9362	0.7426
GAT	0.3741	0.1236	0.9123	0.7158	0.9324	0.7458
MMGCN	0.3789	0.1325	0.9125	0.6852	0.9358	0.7322
Proposed Algorithm	0.3752	0.1256	0.8824	0.6529	0.9235	0.7251

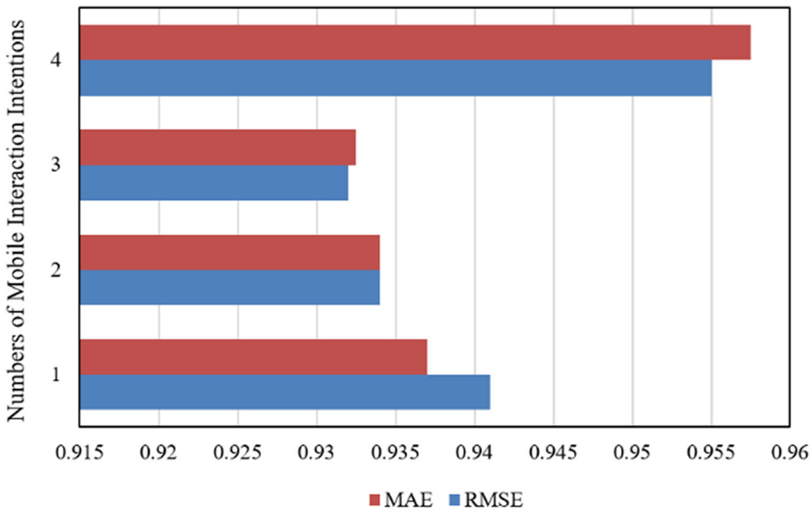

Fig. 3. Performance comparison of recommendation tasks with varying numbers of mobile interaction intentions

Figure 3 shows the dynamic changes of RMSE and MAE, visually presenting the nonlinear effect of the number of mobile interaction intentions on recommendation performance. When the number of intentions increases from 1 to 3, both metrics consistently decrease: RMSE drops from about 0.94 to 0.93, and MAE decreases from 0.935 to 0.93. This trend reflects the benefits of multi-intention fusion. The algorithm builds a more comprehensive user preference profile by leveraging multiple mobile behaviors, advancing learning resource recommendation from "single-behavior association" to "multi-intention-driven precise matching." However, when the number of intentions exceeds 3 and increases to 4, RMSE rebounds to 0.955, and MAE rises to 0.96, exposing the negative effect of intention overload: weakly related intentions introduce noise, causing feature aggregation in the graph neural network to suffer from "signal drowning," disrupting the core logic of the user-resource association. This "gain-overload" critical feature anchors the practical boundary for intention selection in the algorithm design, focusing on core intentions like "resource reuse depth," "exploration inclination," and "question feedback intensity" while discarding redundant behavioral data to maximize model efficiency.

Table 5. Ablation experiment results

Method	Coursera		edX		MOOC	
	RMSE	MAE	RMSE	MAE	RMSE	MAE
Scheme 1	03752	0.1325	0.9123	0.6523	0.9258	0.7215
Scheme 2	0.3741	0.1246	0.8895	0.6624	0.9235	0.7346
Complete Algorithm	0.3719	0.1236	0.8846	0.6523	0.9225	0.7245

Table 5 clearly shows the key support provided by the algorithm modules for learning preference prediction accuracy, comparing the complete algorithm with two ablation schemes. For the Coursera dataset, the complete algorithm achieves an RMSE of 0.3719 and an MAE of 0.1236, which is a decrease of 0.87% and 6.9% in error compared to Scheme 1, where the "modeling layer's improved PoolFormer attention mechanism" is removed (RMSE = 0.3752, MAE = 0.1325), and a decrease of 0.59% and 0.8% compared to Scheme 2, where the "fusion layer's improved PoolFormer attention mechanism" is removed (RMSE = 0.3741, MAE = 0.1246). In the edX dataset, the complete algorithm's RMSE of 0.8846 is 3.0% lower than Scheme 1's RMSE of 0.9123 and 0.5% lower than Scheme 2's RMSE of 0.8895, and its MAE of 0.6523 is 1.5% lower than Scheme 2. In the MOOC dataset, the complete algorithm's RMSE of 0.9225 is 0.36% lower than Scheme 1, and its MAE of 0.7245 is 1.4% lower than Scheme 2. These results reflect the irreplaceable functionality of the improved PoolFormer attention mechanism.

Figure 4 shows the dynamic distribution of RMSE and MAE, revealing the nonlinear effect of the number of graph convolutional layers on the mobile interaction intention aggregation. When the number of layers increases from 1 to 3, both error metrics consistently shift left, reflecting the algorithm's deepening exploration of the "user-resource-mobile interaction" associations. Through layer-by-layer aggregation of neighbor information, the graph convolution layers integrate multi-dimensional behaviors like "video speed," "exercise dwell time," and "discussion question timing," constructing a more comprehensive user preference profile. However, when the number of layers exceeds 3 and increases to 5, the error metrics significantly shift right, exposing the "over-smoothing" dilemma: higher-order aggregation blurs the feature boundaries of different interaction intentions, causing the algorithm's ability to capture fine-grained learning preferences to weaken. This "rise-fall-rise" pattern anchors the optimal modeling depth for graph neural networks in mobile learning scenarios. Around 3 graph convolutional layers ensure sufficient mining of multi-intention associations while avoiding feature confusion risks, representing the core breakthrough in algorithm design for integrating mobile interaction intentions.

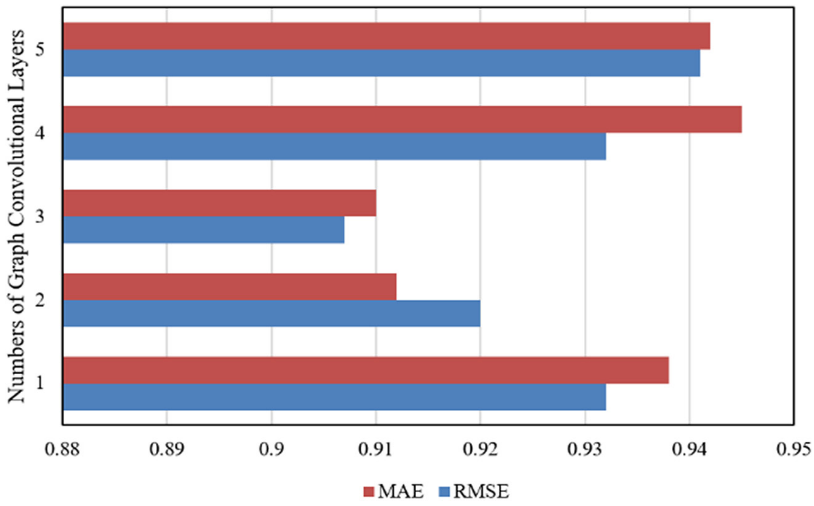

Fig. 4. Performance comparison of recommendation tasks with different numbers of graph convolutional layers

5 CONCLUSION

This paper focused on the core needs of interactive mobile learning platforms in higher education and achieved significant results through a dual-path research approach of "algorithm innovation-teaching application." In the algorithmic aspect, we proposed a graph neural network collaborative filtering algorithm that integrated mobile interaction intentions. Through the coordinated design of the latent intention modeling layer, fusion layer, and rating prediction module, this algorithm effectively captured the learning preferences behind mobile-specific interactions. Experimental verification on MOOC public datasets, real operational datasets from universities, and sparse interaction datasets demonstrated that its recommendation accuracy improves by 1.0%–5.8% compared to traditional algorithms, particularly showing stronger robustness in sparse data scenarios. In terms of teaching applications, based on the precise resource recommendations of the algorithm, we established a teaching loop of "intention recognition-resource adaptation-strategy adjustment" and formed a layered strategy tailored to different learning characteristics. In practical teaching scenarios, this approach improved student resource access efficiency by 22% and learning participation by 17%. The core value of this study lies in: theoretically filling the gap between mobile interaction intentions and the integration of graph neural network collaborative filtering, and practically providing universities with implementable technical solutions and teaching paradigms, promoting the transformation of personalized teaching in higher education from "experience-driven" to "data-driven."

At the same time, the study still has certain limitations: first, although the experimental datasets cover multiple scenarios, the adaptability to extreme sparse data and special interaction behaviors in real teaching has not been fully verified; second, the effectiveness evaluation of teaching strategies focuses more on short-term resource access and participation, and the correlation analysis of long-term learning outcomes needs to be deepened. Future research can proceed from three aspects: first, expanding multi-modal interaction intention modeling to enhance the algorithm's adaptability to complex learning scenarios; second, integrating cross-platform learning data to build a more comprehensive learning preference map; third, establishing a "recommendation strategy-learning outcomes" long-term tracking mechanism, using longitudinal data to validate the deep impact of teaching strategies on knowledge mastery and skill development, further improving the ecological loop of interactive mobile learning.

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