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PAPER

Intelligent Education Based on Mobile Learning: Transitioning from Traditional Classrooms to Adaptive Learning Environments

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ABSTRACT

With the rapid development of information technology, mobile learning has become a key means to enhance educational quality and facilitate personalized learning. Traditional classroom teaching models exhibit limitations in terms of personalization, adaptability, and flexibility. Mobile learning, on the other hand, offers the opportunity for learning anytime and anywhere, addressing the individualized needs of students. However, effectively integrating mobile learning with intelligent education technologies to create learning environments that cater to diverse student needs remains a significant challenge in current educational research. In response, an intelligent education framework based on mobile learning was proposed in this study. This framework aims to drive the transition of education from traditional classrooms to adaptive learning environments by integrating heterogeneous network graphs and students' personalized preferences. The primary focus of this study includes two parts: first, a method for constructing heterogeneous network graphs based on mobile learning, which seeks to enhance the adaptability of learning environments through multi-source data fusion; second, the personalized integration of long- and short-term preferences, along with an interest recommendation mechanism, using intelligent algorithms to provide customized learning path recommendations for students. Through these two aspects, the study seeks to offer effective solutions for the transformation of intelligent education, promote the practical application of personalized learning systems, and provide theoretical support and practical guidance for the development of educational technologies.

KEYWORDS

mobile learning, intelligent education, heterogeneous network graphs, personalized recommendations, adaptive learning environments, student preferences

1 INTRODUCTION

With the rapid advancement of information technology, the education sector is undergoing profound transformation. From traditional classroom teaching models

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to personalized learning environments driven by intelligent technologies [1–3], intelligent education has emerged as a crucial trend in global educational reform [4, 5]. In particular, the widespread adoption of mobile learning has made learning more flexible and personalized, enabling students to access educational resources anytime and anywhere. This has significantly enhanced student autonomy and engagement in the learning process [6–10]. However, traditional classroom models have limitations in terms of personalizing and adapting teaching outcomes. The effective integration of mobile learning and personalized recommendations has become key to improving the quality of education.

This study aims to explore how the combination of mobile learning and intelligent technologies can facilitate the intelligent transformation of educational environments. Research has shown that, with the continuous progress of technology, education systems based on big data and artificial intelligence can offer personalized learning recommendations and services based on students' learning progress, interests, preferences, and individual differences [11–15]. Despite the achievements in intelligent education, many scholars still face significant challenges in integrating mobile learning with intelligent educational environments and in the implementation of personalized recommendation systems [16, 17]. Most existing educational platforms focus primarily on automating classroom instruction or conducting basic learning behavior analysis, neglecting the optimization of personalized learning paths based on students' short- and long-term preferences, and failing to adequately address the dynamic nature of students' interests.

Although considerable progress has been made in data processing and algorithm optimization for personalized learning recommendations, existing methods have yet to fully account for the influence of students' learning needs at different stages, emotional fluctuations, and environmental factors on their learning preferences [18–20]. Moreover, the construction of mobile learning heterogeneous network graphs and the integration of students' personalized preferences still lack effective theoretical frameworks and practical guidance. Much of the research in this area has remained at the stage of theoretical model construction and preliminary validation, without delving into systematic studies or providing practical implementation solutions.

This study introduces a method for building heterogeneous network graphs to enhance mobile learning by integrating multi-dimensional information, which helps provide more accurate support for students' learning processes. Additionally, it explores how to personalize recommendations for learning paths by combining students' short-term and long-term preferences as they move from traditional to adaptive learning environments. Using machine learning and data mining, the study offers dynamic, personalized learning recommendations. The innovation of this study is in developing an intelligent learning framework that improves learning outcomes and supports the advancement of intelligent education.

2 CONSTRUCTION OF MOBILE LEARNING HETEROGENEOUS NETWORK GRAPHS

In traditional classroom learning, students primarily rely on the content delivered by instructors and textbooks. However, in adaptive learning environments, students are required to autonomously select learning resources and create learning plans to meet their personalized learning needs. To address the core issue of how to smoothly transition from traditional classroom models to personalized, adaptive learning environments in the context of intelligent education transformation, a student short- and long-term preference learning algorithm based on heterogeneous graphs was proposed in this study. The construction of the heterogeneous graph was based on mobile learning networks. In mobile learning environments, students can interact not only with instructional content but also with various other types of nodes, such as learning platforms, other learners, and instructors, forming a multi-dimensional interactive network. By constructing heterogeneous graphs, the relationships between these different types of nodes can be modeled within the graph structure. Through the message-passing mechanism of graph neural networks, higher-order relationships between nodes can be captured, allowing for the identification of the short- and long-term preference characteristics exhibited by students in both classroom learning and adaptive learning environments. Figure 1 provides a schematic of the mobile learning heterogeneous network graph.

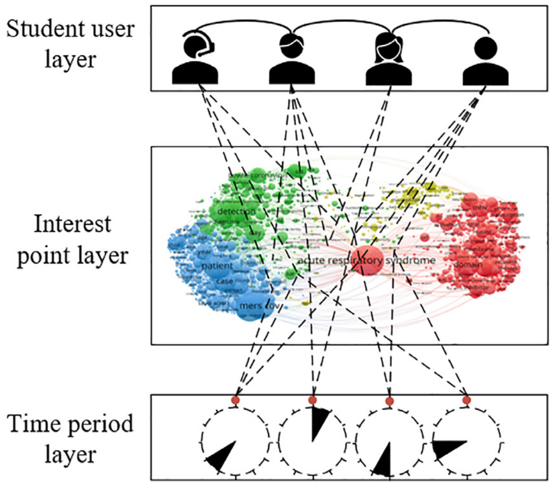

Fig. 1. Schematic of the mobile learning heterogeneous network graph

To abstract the mobile learning network dataset into a graph network, a "student-adaptive learning interest point-time period" heterogeneous graph $\rho = (I \cup M \cup S, R, Q)$ was introduced to simulate the sequential check-ins of students and their mobile learning interactions. The three types of nodes—students I, adaptive learning interest points M, and time periods S—represent the students, their areas of interest in learning content, and the temporal attributes of their learning behaviors, respectively. By representing these entities and their multiple relationships within a graph structure, a more accurate capture of the dynamics of student learning and the evolution of preferences can be achieved. The edges R_{im} between students and adaptive learning interest points indicate the students' visits to specific learning points, effectively reflecting the content that students focus on during classroom or adaptive learning sessions. In addition, the edges R_i between students highlight the common learning behaviors within the social network, suggesting potential collaboration and knowledge sharing among peers. The inclusion of time periods, represented by R_{ms}, enables the graph to capture the students' learning preferences and states at different time points, thereby emphasizing the temporal nature of students' learning behaviors.

2.1 Modeling the "student-adaptive learning interest point" relationship

Based on the analysis of student check-in frequency, it can be observed that students tend to repeatedly visit learning interest points they have encountered multiple times. Consequently, the relationship between students and adaptive learning interest points can be represented by the frequency with which a student accesses these points. In the heterogeneous graph, this relationship is reflected through the edge weights. Specifically, the weight between student i and interest point m is determined by the frequency with which student i visits interest point m. The higher the visit frequency, the greater the weight, indicating a stronger preference of student i for interest point m. Let the set of all adaptive learning interest points be denoted as M, the number of visits of student i to interest point m be represented as $FR(i, m)$, and the total number of visits by student i to all adaptive learning interest points be represented as $FR(i, M)$. The weight between student i and adaptive learning interest point m can be formally expressed as:

$$q_{i,m} = \frac{FR(i,m)}{FR(i,M)} \tag{1}$$

2.2 Modeling the "adaptive learning interest point-adaptive learning interest point" relationship

Considering the sequential effect of student check-in behaviors, where the most recent check-in is given more weight in influencing student preferences, it becomes crucial to model the sequential relationship between adaptive learning interest points. In the student check-in trajectory, two consecutive check-ins are influenced not only by the time interval $\Delta s^i_{j,j+1}$, but also by the state change $Z^i_{j,j+1}$ between learning interest points. Therefore, to accurately model students' learning behaviors, it is necessary to establish a time-sequenced weight strategy. This strategy assigns higher weight to check-ins with shorter time intervals by calculating the time interval of continuously visiting adaptive learning interest points by students, reflecting short-term fluctuations in student preferences. Additionally, the state change $Z^i_{j,j+1}$ in the sequential relationship reveals the transition pattern of interest points between consecutive check-ins, further enhancing the ability to capture students' personalized needs. Let the predefined time threshold be denoted as φ, as defined by the following:

$$Z^i_{j,j+1} = \begin{cases} 1 & IF \Delta s^i_{j,j+1} < \varphi \\ 0 & ELSE \end{cases} \tag{2}$$

Given the edge $r_{u,k}$ from adaptive learning interest point m_u to adaptive learning interest point m_k, the weight considering the sequence effect can be calculated as follows:

$$q^{(SE)}_{u,k} = \sum_{i \in I} \sum_{j=1}^{|z_i|-1} Z^i_{j,j+1}, \quad IF\ n_j = n_u \quad AND \quad n_{j+1} = n_k \tag{3}$$

From the above equation, the weight $q^{(SE)}_{u,k}$ of the edge from m_u to m_k is equal to the total number of times all students transition from m_u to m_k in their check-in trajectories.

In addition to the temporal sequential relationship, geographical distance plays a significant role in student learning behavior, particularly regarding the spatial effects between adaptive learning interest points. Research indicates that students tend to visit adaptive learning interest points that are geographically closer to their current location, and the distribution of this behavior follows a power-law pattern.

Therefore, when constructing the heterogeneous graph for the mobile learning network, the impact of geographical factors on student learning trajectories must be considered. Thus, the geographical distance between adaptive learning interest points visited by students should be an important dimension in the weight strategy. In this strategy, the closer the distance between two interest points, the more likely students are to visit them, and the greater the weight. Let the set of neighboring interest points of adaptive learning interest point m_u in $R_{mm'}$ be denoted as $V(m_u)$, the Euclidean distance between adaptive learning interest points m_u and m_k be denoted as $f^{v}_{u,k}$, and the negative exponent be represented by v.

$$q^{(GE)}_{u,k\ u,k} = \frac{f^{v}_{u,k}}{\sum_{m_j \in V(m_u)} f^{v}_{u,j}} \tag{4}$$

Finally, by combining the sequential effect and the geographical influence, the total weight can be represented as:

$$q_{u,k} = q^{(SE)}_{u,k} \cdot q^{(GE)}_{u,k} \tag{5}$$

2.3 Modeling the "student-student" relationship

Various types of social relationships exist between students, such as friendships, family connections, and classmate relationships, all of which can significantly influence students' preferences for adaptive learning interest points. For example, students may be more inclined to access learning content recommended by close friends, family members, or classmates. In the heterogeneous graph, the relationship between students can be represented by edges, where the weight of each edge reflects the closeness or interaction frequency between the students. Specifically, a weight strategy based on mobile interaction frequency can be established, which transforms interaction records between students into weights to measure the extent to which one student's learning interests are influenced by others. In cases where students exhibit stronger mobile interaction relationships, the likelihood of mutual influence on their preferences for adaptive learning interest points increases. Therefore, in the graph, the weight of the edge between these students should be greater to better reflect their similarity in learning behavior. Specifically, let a very small floating-point number be denoted as γ. The number of times student i_u accesses adaptive learning interest point m is denoted as $d_{i_{u,m}}$, and the total number of accesses by student i to adaptive learning interest points is represented by m. The number of adaptive learning interest points accessed by both student i_u and student i_k is denoted as $\left|M_{i_u} \cap M_{i_k}\right|$. Given the edge $q_{u,k}$ from student i_u to student i_k, its weight can be calculated as follows:

$$q_{u,k} = \frac{\gamma + \sum MIN\left(d_{i_{u,m}}, d_{i_{k,m}}\right)}{\left|M_{i_u} \cap M_{i_k}\right| + 1} \tag{6}$$

2.4 Modeling the "adaptive learning interest point-time period" relationship

Time significantly influences human behavior in learning, affecting students' preferences and patterns. For example, during class hours, students may focus on course-related content, while extracurricular hours are often spent on hobbies or personal learning goals. To capture this time dependency in a heterogeneous graph, a weighting strategy can be used to reflect students' preferences for learning points at specific times. Specifically, the "student-learning interest point" relationships can be weighted based on sign-in times, using time periods and weekdays to dynamically adjust the likelihood of accessing certain interest points. For example, in the morning, students may be more inclined to engage in review-type learning tasks, while in the evening, they may focus more on entertaining or relaxing learning activities. Specifically, let the total number of visits made by all students to adaptive learning interest point m during time period s be represented by $FR\ (I, 1, s)$. The total number of visits by all students to adaptive learning interest point m is also denoted by $FR\ (I, 1, s)$. Given the edge $r_{m,s}$ from adaptive learning interest point m to time period s, its weight can be calculated as follows:

$$q_{m,s} = \frac{FR(I,m,s)}{FR(I,m,S)} \tag{7}$$

3 PERSONALIZED LEARNING PREFERENCES AND RECOMMENDATIONS FROM CLASSROOM TO ADAPTIVE ENVIRONMENTS

3.1 Embedding layer

Figure 2 illustrates the overall architecture of the student long- and short-term preference learning model based on heterogeneous graphs. In the model, the core function of the embedding layer is to transform students, adaptive learning interest points, and categories from discrete scalar representations into low-dimensional embedding vectors, thereby enhancing the model's ability to express student behaviors, learning preferences, and interest points.

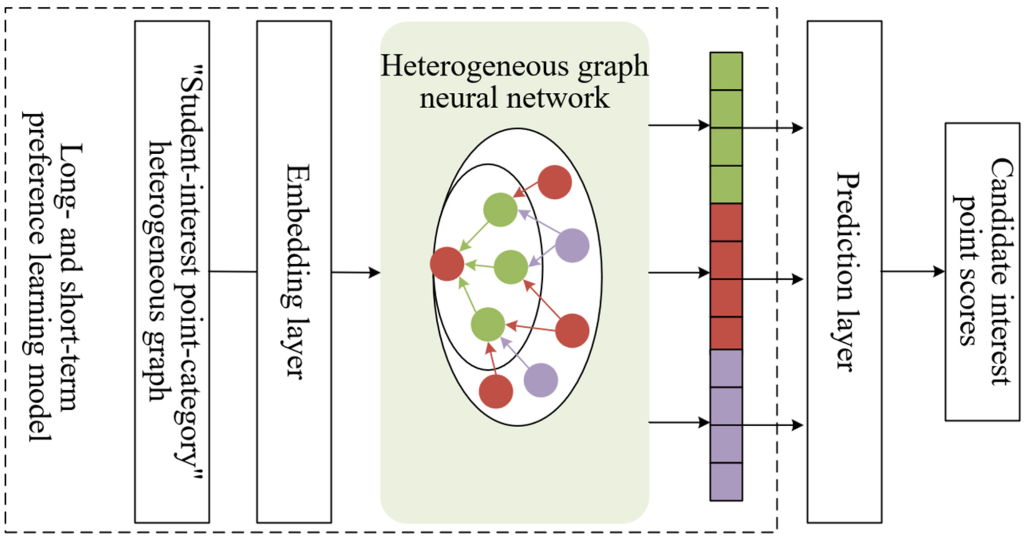

Fig. 2. Overall architecture of the student long- and short-term preference learning model based on the heterogeneous graph

Specifically, the student, adaptive learning interest points, and category information are mapped into embedding vectors through the student embedding transformation matrix, the adaptive learning interest point embedding transformation matrix, and the category embedding transformation matrix, respectively. These embedding vectors capture the latent features and relationships of each element. For instance, the student's embedding vector, r^i, represents the student's long-term learning preferences, while the interest point's embedding vector, r^m, reflects the characteristics of the learning interest point. Through this mapping, the model can effectively represent each node in a low-dimensional space, supporting subsequent graph-based recommendation algorithms for predicting student learning interests and behaviors. For long-term preference learning, the output of the embedding layer consists of the latent representations of the student and interest points. These representations provide the necessary input for subsequent recommendation systems, helping the model understand the student's long-term preferences for adaptive learning interest points.

For short-term preference learning, the embedding layer dynamically adjusts the student's interest representation by integrating each sign-in information from the student's historical trajectory. Specifically, in the short-term preference recommendation task, the student's sign-in behavior reflects their instantaneous learning interests, and the output of the embedding layer is a combination of the student embedding vector and the interest point embedding vector. For each sign-in e, the output of the embedding layer is the sum of the student and interest point embedding vectors, $r^e = r^i + r^m$. This operation combines the student's long-term interest r^i and the instantaneous attraction r^m of the specific interest point, generating a personalized representation for each sign-in. The student's historical trajectory, consisting of v sign-ins, is sequentially stacked together to form the student's trajectory embedding matrix $R^i = \{r^{e1}, r^{e2}, \ldots, r^{ev}\}$, which provides a sequential representation of the student's short-term interest evolution for subsequent models.

3.2 Heterogeneous graph neural network

The heterogeneous graph neural network designed for student long- and short-term preference integration and interest point recommendation leverages diverse relationships between nodes in the graph, such as the "student-interest point" relationships and "category-interest point" relationships. By traversing different types of edges, information fusion is facilitated, allowing for the effective capture of complex correlations between nodes. Figure 3 illustrates the schematic structure of the constructed heterogeneous graph neural network.

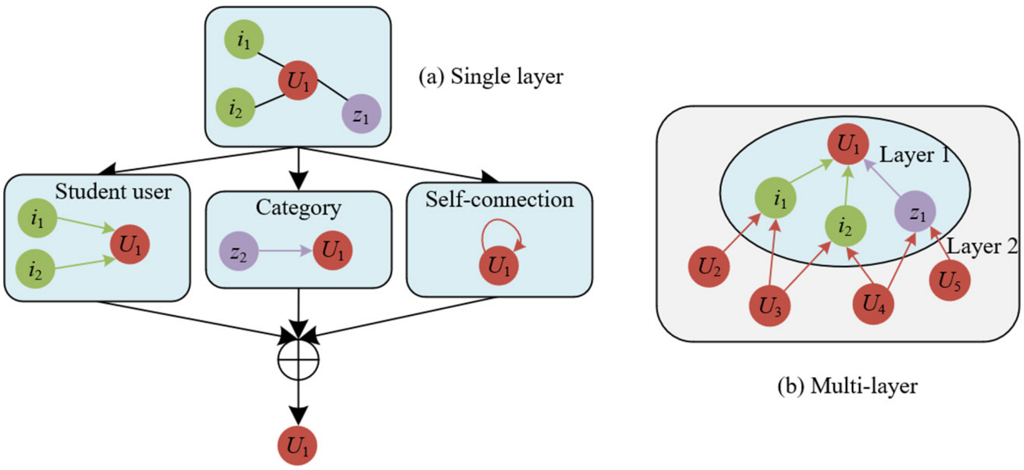

Fig. 3. Schematic structure of the heterogeneous graph neural network

To overcome the computational overhead and efficiency issues caused by the disparity in the number of neighbors of the nodes in the graph, a sampling strategy was proposed in this study, where a fixed number of neighbors are uniformly selected for each node for information propagation, rather than using all neighboring nodes. Student check-in data typically follows a long-tail distribution, where certain interest points receive a large number of student check-ins, while others are rarely visited by students. This uneven distribution of neighbors makes it computationally inefficient to use all neighbors directly. By sampling a fixed number of neighbors, the model can effectively reduce computational complexity while ensuring sufficient information propagation and improving computational efficiency. During the information propagation phase, a node updates its representation by aggregating messages from its neighbors. For instance, the adaptive learning interest point node receives information from the connected student and category nodes and updates itself by combining this information with its own representation. Moreover, to preserve the original information of the nodes, each node is introduced with a self-connection, which ensures the fidelity of the information and prevents the loss of the node's intrinsic features during the update process. Specifically, let the original representation of node u be denoted as g_u, the updated representation of node u be denoted as g'_u, the set of neighbors of node u in relation e be denoted as V_s^e, and the transformation matrix for relation e be denoted as Q_e. The update computation for each node, through aggregating information from its neighbors during the information aggregation phase, is given by the following equation:

$$g'_u = Q_p g_u + \sum_{e \in E} \sum_{k \in V_u^e} \frac{1}{\left|V_u^e\right|} Q_e g_k \tag{8}$$

To capture richer high-order relationships between nodes, the model extends the depth of information propagation through a multi-layer structure, enabling the effective capture of second-order and higher-order dependencies between nodes. A single-layer graph neural network can only learn the relationships between nodes and their immediate neighbors, which limits its ability to model complex student behavior patterns and interest changes. In recommendation systems, particularly when students' long-term preferences and transient interests are driven by multi-level and multi-dimensional relationships, single-layer models are inadequate in comprehensively reflecting these intricate dependencies. Therefore, the proposed approach extends the graph neural network from a single-layer to a multi-layer architecture. Through multiple rounds of information propagation and aggregation, nodes can interact not only with their direct neighbors but also indirectly perceive the information of distant nodes through multi-hop neighbors. For example, student node i_1 and category node z_1 can obtain information from their respective neighbors m_2 and m_5 through the second-order propagation paths $m_2 \Rightarrow i_1 \Rightarrow m_1$ and $m_5 \Rightarrow z_1 \Rightarrow m_1$, and then propagate this information to the target interest point m_1, ultimately helping m_1 capture the representation of second-order neighbors that are similar to it. Let the representation of node u in the m-th layer be denoted as $g_u^{(m)}$, the transformation matrix for relation e in the m-th layer be denoted as $Q_e^{(m)}$, and the activation function be denoted as δ. After the aggregation through m layers, the update formula for each node is given by the following equation:

$$g_u^{(m)} = \delta\left(Q_p^{(m)} g_u^{(m-1)} + \sum_{e \in E} \sum_{k \in V_u^e} \frac{1}{\left|V_u^e\right|} Q_e^{(m)} g_k^{(m-1)}\right) \tag{9}$$

3.3 Prediction layer

The core function of the prediction layer in the model is to compute the preference score of each candidate adaptive learning interest point within the set of candidate interest points, thereby providing a basis for personalized recommendations. The objective of this process is to capture both the long- and short-term preferences of students and assess the degree of interest a student may have for each interest point. First, based on the embedding vectors of students and interest points, as well as the node representations obtained after multi-layer propagation in the heterogeneous graph, a certain prediction function is applied to compute the preference score for each candidate interest point. This score reflects the level of interest or preference a student has for a specific adaptive learning interest point. A higher score indicates that the student is more likely to take an interest in or engage in learning activities related to that interest point. Let the vector representations of student i_u, candidate adaptive learning interest point m_k, and the category z_{jj} of the candidate adaptive learning interest point in the final layer of the heterogeneous graph neural network be denoted as g_{iu}, g_{uk}, and g_{zj}, respectively. The preference vector of student i_u for candidate adaptive learning interest point m_k is denoted as $o^t_{iu,mk}$. The embedding vector of the candidate adaptive learning interest point m_k is denoted as r^{mk}. The long-term adaptive learning interest point preference weight, long-term category preference weight, and short-term preference weight of the student are denoted as η_{iu}, ω_{iu}, and ε_{iu}, respectively. The preference score $b_{u,k}$ for student i_u with respect to candidate adaptive learning interest point m_k can be calculated using the following formula:

$$b_{u,k} = \eta_{i_u} \cdot g_{i_u} \cdot g_{m_k} + \omega_{i_u} \cdot g_{i_u} \cdot g_{z_j} + \varepsilon_{i_u} \cdot o^t_{u,k} \cdot r^{m_k} \tag{10}$$

3.4 Loss function

In order to effectively capture both the long- and short-term preferences of students, an improved cross-entropy loss function was designed in this study. This loss function optimizes the model's immediate response to short-term preferences as well as its global modeling ability for long-term preferences. Let the training set in the student sign-in data be denoted as T, the target adaptive learning interest points as o, and the negative samples, sampled from unvisited adaptive learning interest points, as v_j. The loss function is expressed as:

$$LOSS = -\sum_{t_i \in T} \left(\log \delta(b_{i,o}) + \sum_{j=1}^{J} \left(\log\left(1 - \delta\left(b_{i,v_j}\right)\right)\right)\right) \tag{11}$$

Additionally, to further enhance the convergence speed and training stability of the model, the Adam optimizer was employed for optimizing the model parameters. The Adam optimizer combines momentum and adaptive learning rate adjustment methods, efficiently addressing sparse gradient issues and oscillations commonly encountered during the optimization process. By adaptively adjusting the learning rate of each parameter, the Adam optimizer enables the model to update parameters dynamically during different stages of training, thereby preventing the gradient vanishing or explosion issues often faced by traditional optimization algorithms when dealing with complex heterogeneous graph data. By integrating the improved cross-entropy loss function with the Adam optimizer, the model is able to efficiently capture both the long- and short-term preferences of students during the training process while also improving the accuracy and generalization capability of the recommendation system.

4 EXPERIMENTAL RESULTS AND ANALYSIS

The experimental results presented in Figure 4 clearly demonstrate that the proposed method outperforms the two comparative methods—those that do not consider sequential effects and those that disregard geographical distance—on both the training and validation sets. Specifically, in the training set, the proposed method shows higher values across metrics such as Rec@5, Rec@10, NDCG@5, and NDCG@10. Notably, the Rec@5 value reaches 0.225, compared to 0.15 for the "no sequential effects" method and 0.105 for the "no geographical distance" method. Furthermore, on the validation set, the proposed method continues to exhibit superior performance, with higher values in Rec@5, Rec@10, NDCG@5, and NDCG@10, particularly achieving the highest Rec@5 and Rec@10 scores among all comparative methods. In contrast, although the methods that ignore sequential effects and geographical distance show some improvement on the validation set, they still fail to surpass the proposed method, with a notable gap observed in NDCG@10. These results indicate that both sequential effects and geographical distance have significant impacts on personalized recommendations for students. More specifically, by incorporating sequential effects and geographical factors, the proposed method more accurately captures students' learning behavior patterns, thus surpassing the recommendation accuracy of the comparative methods that rely solely on other factors.

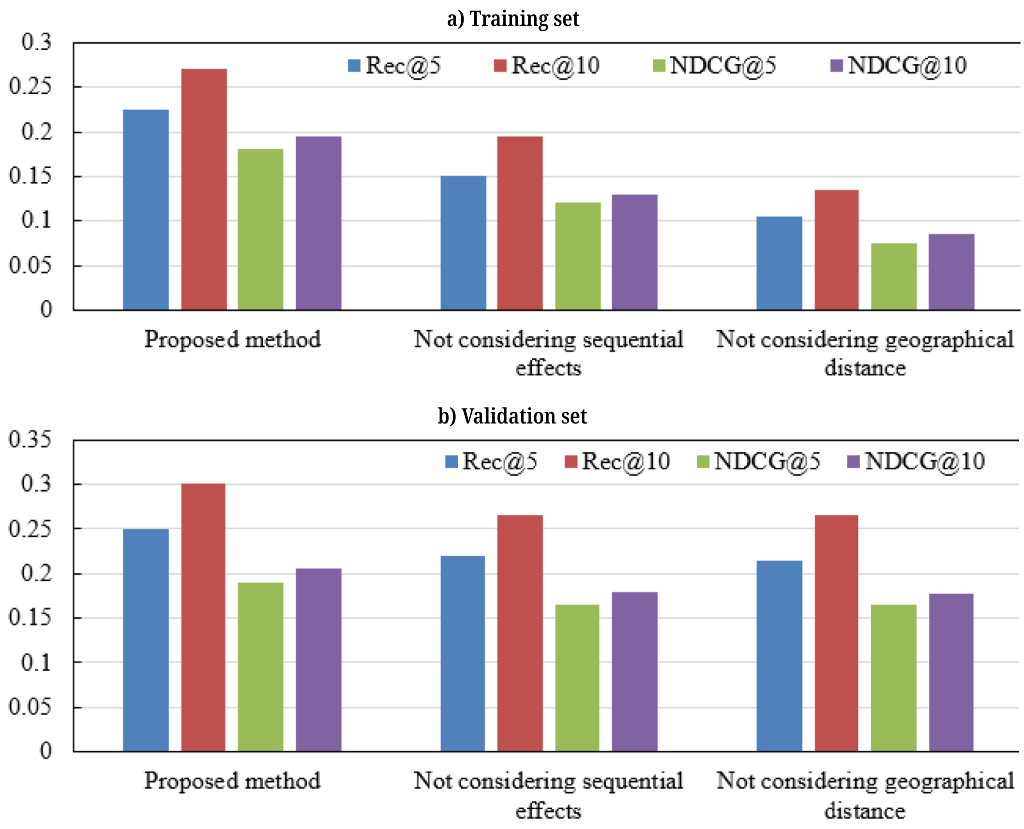

Fig. 4. Comparison of experimental results of the proposed method and the methods not considering sequential effects or geographical distance

According to the experimental results presented in Figure 5, the proposed method demonstrates a certain level of stability in the Recall@5 and NDCG@5 metrics on the training set as the dimensionality varies. For the Recall@5 metric, as the dimensionality increases from 200 to 700, the performance remains relatively steady, with Recall@5 values gradually rising from 0.248 to 0.252, showing only a modest increase. The increase in dimensionality does not result in a significant performance improvement. Similarly, for the NDCG@5 metric, the values exhibit a similar trend, increasing from 0.1945 to 0.198, with only a slight overall improvement. Despite the increase in performance with higher dimensions, the change is not substantial, indicating that within a certain range, further increasing dimensionality has reached a point of diminishing returns in terms of performance improvement. These experimental results suggest that the model shows a certain degree of stability on the training set. Although increasing the dimensionality has led to some improvement in performance, the effect has become marginal. This implies that the proposed method based on mobile learning and the construction of a heterogeneous graph has reached an ideal state in terms of capturing students' long-term and short-term preference features.

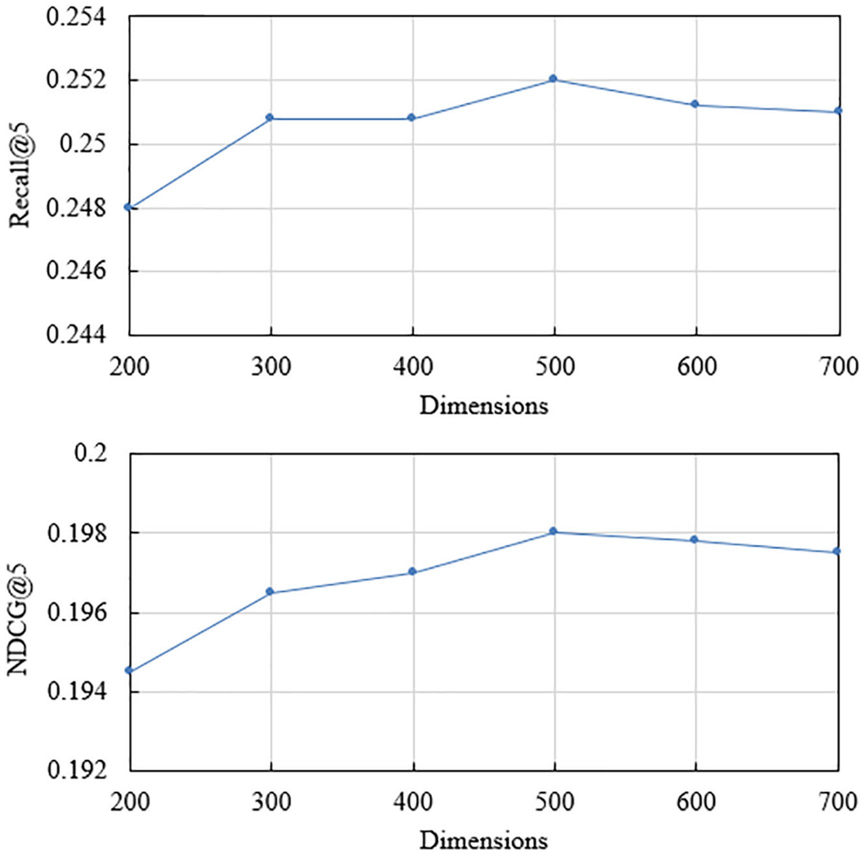

Fig. 5. Performance of the proposed method on Recall@5 and NDCG@5 in the training set

As shown in the experimental results in Figure 6, the proposed method demonstrates a slight improvement in Recall@5 and NDCG@5 on the test set as the dimensionality increases, though the overall improvement is relatively modest. For the Recall@5 metric, as the dimensionality increases from 200 to 700, performance gradually improves, rising from 0.337 to 0.3432, with an increase of 0.0062. This indicates some improvement, but the growth is relatively steady. Similarly, for the

NDCG@5 metric, an increase in dimensionality from 200 to 700 results in a similar trend, with values increasing from 0.245 to 0.258, an overall improvement of 0.013. This suggests that increasing the dimensionality contributes to enhancing the quality of the recommendations, particularly in terms of ranking accuracy. Although the performance improvement is not substantial, it can be observed that higher dimensionality does contribute to the precision of the recommendation outcomes, implying that additional feature dimensions may help to capture students' interests and needs more accurately. The analysis reveals that the proposed method demonstrates stable performance improvements on the test set, particularly in terms of Recall@5 and NDCG@5. As the dimensionality increases, the accuracy of recommendations and the quality of rankings are slightly optimized. This indicates that with the introduction of multi-dimensional information in the construction of the heterogeneous graph, the model can more precisely capture students' long- and short-term preferences, thereby providing more personalized learning resource recommendations.

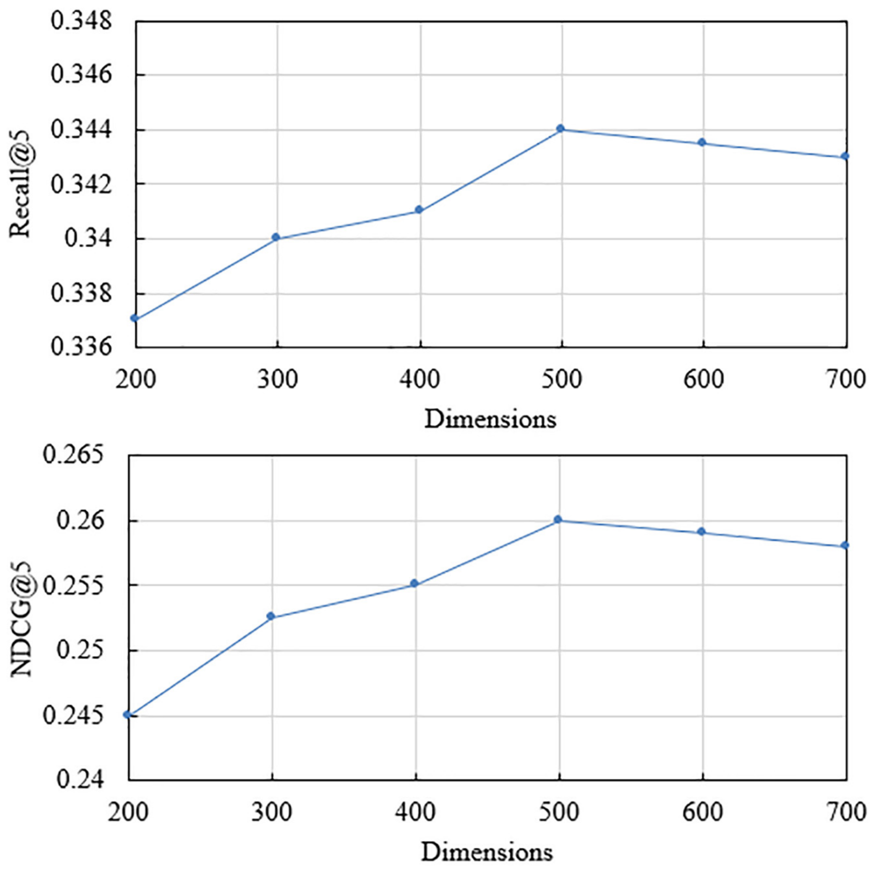

Fig. 6. Performance of the proposed method on Recall@5 and NDCG@5 in the test set

As shown in Table 1, the proposed method outperforms other recommendation algorithms across all metrics in both the training and test sets. On the training set, the proposed method achieves higher Recall@5 (0.2456) and Recall@10 (0.3125) compared to DeepWalk (0.1895 and 0.2325), Graph Sample and Aggregation (GraphSAGE) (0.1852 and 0.2451), and other methods. Additionally, it demonstrates a significant advantage in NDCG@5 (0.1895) and NDCG@10 (0.2236). On the test set, the proposed method also leads in performance, especially in Recall@5 (0.3212) and Recall@10 (0.4125), showing notable advantages over Deep Structured Semantic Model (DSSM) (0.3125 and 0.3895) and Deep Q-Network (0.3262 and 0.4125).

Furthermore, the proposed method achieves higher values in NDCG@5 (0.2452) and NDCG@10 (0.2785) compared to most of the competing models, indicating better recommendation accuracy and ranking precision.

Table 1. Performance comparison of different recommendation algorithms

Model	Training Set				Test Set			
	R@5	R@10	N@5	N@10	R@5	R@10	N@5	N@10
DeepWalk	0.1895	0.2325	0.1325	0.1452	0.3125	0.4125	0.2315	0.2451
GraphSAGE	0.1852	0.2451	0.1322	0.1562	0.3256	0.4232	0.2345	0.2652
DSSM	0.2236	0.2789	0.1789	0.1895	0.3125	0.3895	0.2325	0.2595
Deep Q-Network	0.2234	0.2785	0.1784	0.1874	0.3262	0.4125	0.2458	0.2625
Policy Gradient	0.1562	0.2236	0.1325	0.1236	0.3125	0.3895	0.2232	0.2321
Domain Adaptation	0.2125	0.2541	0.1658	0.1874	0.2236	0.2895	0.1895	0.2125
Proposed method	0.2456	0.3125	0.1895	0.2236	0.3212	0.4125	0.2452	0.2785

Based on the comparative analysis of the experimental results, it is evident that the proposed method outperforms most other recommendation algorithms across all metrics, particularly in Recall@5 and Recall@10 on both the training and test sets. This indicates that the proposed method, which is based on mobile learning and the construction of heterogeneous network graphs, demonstrates a significant advantage in accurately recommending learning resources and paths for students. By integrating multi-dimensional information and employing a personalized recommendation mechanism, the model is able to more precisely capture students' interests and learning preferences, thus enhancing the recommendation performance. In contrast, other algorithms, such as DeepWalk, GraphSAGE, and DSSM, while performing well, do not achieve the same level of performance as the proposed method, particularly in terms of the normalized discounted cumulative gain (NDCG) metric, where the ranking quality is significantly improved. Additionally, the superiority of the proposed method on the test set suggests that the model exhibits strong generalization ability and robustness, enabling it to adapt to dynamic changes in real-world applications. Overall, the proposed method not only improves the accuracy of recommendations but also enhances the precision of rankings, providing robust support for the realization of personalized and intelligent learning path recommendations.

5 CONCLUSION

Focusing on intelligent education based on mobile learning, two core methods were proposed in this study. First, a heterogeneous network graph construction method based on mobile learning, which provides precise dynamic support through the integration of multi-dimensional information; second, an exploration of the integration of short- and long-term personalized preferences and an interest recommendation mechanism, combining machine learning and data mining techniques to dynamically recommend personalized learning paths in adaptive learning environments. Experimental results demonstrate that the proposed method significantly outperforms other recommendation algorithms in terms of recommendation accuracy and ranking precision, with notable improvements in the recall and NDCG metrics. This indicates that the innovative method presented provides effective support for personalized learning recommendations, with strong application potential.

However, despite the excellent performance of the proposed method, several limitations remain. First, as the data scale and complexity increase, the computational and storage efficiency of the model may become a bottleneck. Second, the interpretability of the model still requires further enhancement to increase user trust and acceptance. Future research could explore the following directions: First, optimizing the construction of the heterogeneous network graph to improve the dynamic adaptability of the model; second, combining reinforcement learning techniques to enhance the modeling ability of short- and long-term preferences; third, improving computational efficiency to support large-scale data processing; and fourth, strengthening the model's interpretability to enhance user experience and system transparency. Overall, the proposed method offers an innovative solution in the field of personalized learning recommendations, with potential for widespread application in intelligent education in the future.

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