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PAPER

Impact of Personalized Learning Paths Supported by Mobile Technology on Student Academic Achievement

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ABSTRACT

With the rapid advancement of mobile technology, mobile learning has become an integral component of modern education, particularly in the design and implementation of personalized learning paths. These paths enable tailored learning content and strategies based on students' interests, abilities, and progress, thereby enhancing knowledge acquisition and improving academic achievement. Recent studies on personalized learning paths have primarily focused on content recommendation and learning outcome assessment, whereas limited attention has been given to student interaction relationships. In mobile learning environments, interactions among students and their mutual influence play a crucial role in optimizing personalized learning paths. However, existing research methodologies predominantly rely on theoretical analysis and static data processing, lacking dynamic modeling of complex student interaction patterns. This study aims to address this gap by analyzing student interactions within personalized learning paths and proposing a relationship discovery model based on an extended mobile interaction graph to help further optimize personalized learning paths. The findings are expected to contribute to the refinement of personalized learning path design and provide educators with real-time data support to enhance student academic achievement. By constructing a more precise interaction relationship discovery model, this study offers a novel theoretical framework and practical guidance for advancing personalized education.

KEYWORDS

mobile learning, personalized learning path, student interaction relationship, extended mobile interaction graph, academic achievement

1 INTRODUCTION

With the rapid advancement of information technology, mobile technology has increasingly permeated the field of education, exerting a profound impact on students' learning methods and academic performance [1–4]. The rise of mobile learning has enabled students to access learning resources and engage in interactive learning anytime and anywhere through smart devices, significantly enhancing both the

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flexibility and personalization of learning [5–9]. However, the effective utilization of mobile technology to support personalized learning paths and its impact on student academic achievement remain critical research topics in education. Personalized learning paths not only allow for the customization of learning content based on students' interests, abilities, and learning progress but also facilitate the development of effective learning strategies at different stages of the learning process.

Existing research has demonstrated that personalized learning paths contribute positively to improving learning outcomes, enhancing motivation, and enriching the learning experience [10, 11]. However, prior studies have predominantly focused on static personalized design and learning assessment, with limited exploration of how dynamic student interactions can further optimize learning paths in mobile learning environments [12–15]. Student interaction plays a particularly crucial role in mobile learning, as students function not only as recipients of learning content but also as disseminators and adjusters of knowledge. Investigating mobile interaction relationships among students can provide more precise data for optimizing personalized learning paths while offering educators more profound insights into student learning behaviors and how to better guide them.

Despite the progress made in this field, several limitations remain in existing research methodologies. On the one hand, many studies have failed to explore the specific patterns and mechanisms of student interactions in mobile learning environments, resulting in a lack of targeted design in personalized learning paths. On the other hand, most existing models have primarily focused on theoretical analyses or static data processing, with insufficient emphasis on dynamic modeling and real-time adjustments for complex student interaction relationships [16–20]. These limitations have constrained the effectiveness and adaptability of current approaches in practical applications.

This study consists of two main components. First, student interactions within personalized learning paths were examined to identify potential challenges in the learning process. Second, an interaction relationship discovery model in the personalized learning paths was constructed based on an extended mobile interaction graph. Through an in-depth analysis of student interaction relationships, this study aims to provide educators with scientifically grounded strategies for designing personalized learning paths, ultimately improving student academic achievement. Additionally, this research is expected to offer new perspectives and methodologies for the academic community, further advancing the practice and development of personalized education.

2 IDENTIFICATION OF MOBILE INTERACTION RELATIONSHIPS AMONG STUDENTS IN PERSONALIZED LEARNING PATHS

In mobile learning environments, real-time communication and collaboration among students are facilitated through smart devices, enabling not only the resolution of learning challenges but also the sharing and deepening of knowledge. When student interaction relationships are effectively identified and understood, educators and learning systems can dynamically adjust and optimize learning paths based on interaction patterns, thereby enhancing the precision of personalized learning path design. For instance, certain students may achieve improved academic performance through group discussions or online collaboration, whereas others may require additional individualized guidance and learning support. Therefore, continuous monitoring of student interaction relationships allows for the provision of targeted educational support, fostering student motivation and ultimately enhancing academic achievement.

In personalized learning paths, mobile interaction relationships among students are not solely reflected in direct interactions but are also significantly influenced by students' personalized attributes and communication dynamics. Personalized attribute information such as interests, subject preferences, and learning styles serves as critical references for educators in understanding students' learning needs and potential interaction patterns. Furthermore, students' contributions to online learning platforms, including discussion posts and engagement in interactive activities, provide essential clues for identifying interaction relationships. These contributions not only reflect students' comprehension and perspectives on specific subjects but also reveal consensus or divergence among peers, offering valuable contextual information for designing personalized learning paths. By analyzing student interactions on learning platforms—such as comments, likes, and replies—the underlying social connections and collaborative learning potential among students can be further explored. Figure 1 presents an illustration of the identification of mobile interaction relationships among students in personalized learning paths.

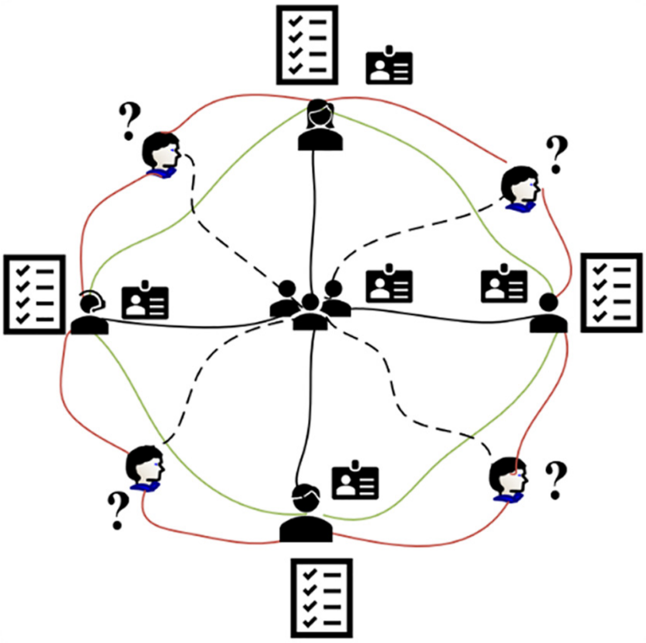


Fig. 1. Identification of mobile interaction relationships among students in personalized learning paths

The research objective was explicitly defined through a formalized description. The identification of student interaction relationships in mobile learning environments involves inferring latent mobile interaction relationships among students based on their attribute information, interaction behaviors, and social network structures within an online mobile interaction network. Specifically, given an online mobile interaction network $H = (N, R^D, R^Z, X)$, the student set N is divided into a set of hidden students $N_{HI} = (n^G_{uk})$ and a set of regular students $N_{NO} = (n^G_{uk})$. Among these students, the mobile interaction relationships of regular students are publicly available, allowing for direct observation of their social interaction patterns. However, the mobile interaction relationships R^D of hidden students remain unknown, though partial interaction relationships R^Z can be inferred from publicly available profile information. The objective is to design an inference function $d(\cdot)$ that accurately predicts and identifies the latent mobile interaction relationships of hidden students using publicly available data, known interaction relationships R^D and R^Z, and partial interaction information of hidden students. Given the attribute matrix X, the inference function can be expressed as follows:

$$d(N, R^D, R^Z, X, \Phi) \rightarrow B \tag{1}$$

The design of personalized learning paths relies on student interaction patterns and social network structures. Therefore, in the identification of mobile interaction relationships, not only direct interaction behaviors but also the influence of students' personalized attributes and communication dynamics must be considered. Under this research framework, an inference model was developed to predict potential interactions between hidden students and other students by utilizing student attribute vectors and their participation in learning discussions or social activities. For instance, hidden students may demonstrate interest in a particular subject or topic through specific communication behaviors, and these interactions can serve as an essential basis for predicting their potential learning collaboration relationships with other students.

3 STUDENT MOBILE INTERACTION RELATIONSHIP DISCOVERY MODEL BASED ON THE EXTENDED MOBILE INTERACTION GRAPH

The framework of the student mobile interaction relationship discovery model, based on the extended mobile interaction graph, was designed to identify latent mobile interaction relationships of hidden students using deep learning methods. The core concept of this model is to integrate student attribute information, communication interactions, and mobile interaction relationships into an extended mobile interaction graph, which is then processed using a Graph Convolutional Network (GCN) for deep learning and relationship inference. Within this framework, the extended mobile interaction graph consists of three distinct types of edges, corresponding to different interaction relationships among students: fundamental attribute relationships, communication interaction relationships, and direct mobile interaction relationships. This graph structure effectively captures the complex multidimensional interaction dynamics among students, thereby providing multi-layered data support for the inference of hidden student interaction relationships. Structurally, the model comprises two main components. The first component is the convolutional network layer, which serves as an encoder responsible for inputting and processing the structural information of the extended mobile interaction graph. The student node embedding representation is learned through graph convolutional operations. The second component is the prediction scoring layer, functioning as a decoder, which utilizes the student node embedding representation obtained from the convolutional network layer to evaluate and predict potential mobile interaction relationships between students. Figure 2 presents the framework of the student mobile interaction relationship discovery model based on the extended mobile interaction graph.

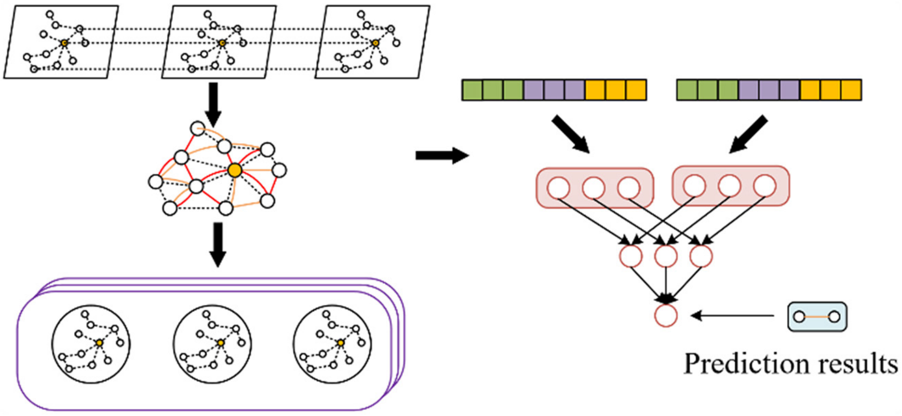


Fig. 2. Framework of the student mobile interaction relationship discovery model based on the extended mobile interaction graph

3.1 Extended social graph

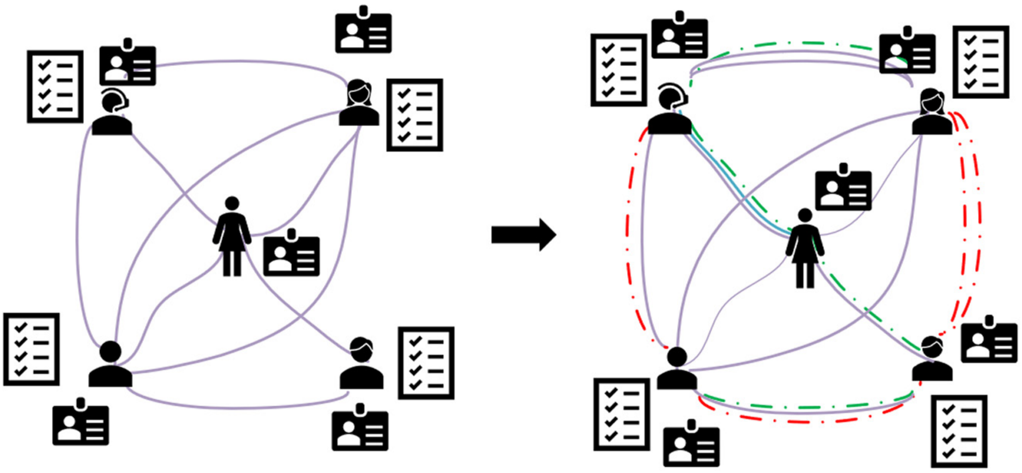


Fig. 3. Schematic representation of the extended social graph

The introduction of the extended mobile interaction graph in the model is intended to comprehensively integrate multidimensional student information, thereby improving the accuracy of predicting latent interaction relationships of hidden students. Traditional mobile interaction networks primarily focus on direct interactions and communication exchanges among students. However, in the design of personalized learning paths, student attribute information also plays a crucial role. Therefore, the network structure was expanded by incorporating attribute association information into the existing mobile interaction relationship network. This enhancement allows the network to capture not only student interaction behaviors but also similarities among students. Specifically, the edge set R of the extended mobile interaction graph consists of three distinct types of edges: R^D, representing mobile interaction relationships; R^Z, denoting communication interaction relationships; and R^X, indicating attribute association relationships based on shared same attribute values among students. The integration of these three relationship types facilitates a more comprehensive representation of potential student interaction patterns, providing enriched information sources to support the identification of hidden student relationships. Figure 3 shows the schematic of the extended social graph.

With the introduction of the extended mobile interaction graph, student relationships are no longer confined to a single-dimensional interaction but can instead be understood through multi-layered associations. By integrating student attribute information with communication and mobile interaction behaviors, the model can more effectively reveal potential learning collaboration relationships among students. For instance, if student i and student n share the same attribute values, an attribute association edge is established between them, introducing a new dimension for identifying potential learning relationships. Furthermore, the model employs the adjacency matrix L and its three submatrices—L_D, L_Z, and L_X—to explicitly define the impact of each relationship type on student interactions. These submatrices correspond to mobile interaction relationships, communication interaction relationships, and attribute association relationships, respectively. This multi-layered graph structure enables the model to capture more complex interaction patterns among students, providing enriched data support for the inference of hidden student interactions. Additionally, the structure enhances the accuracy of personalized learning path recommendations.

3.2 Convolutional network layer

In the model, the initial embedding representation for each student node was defined by encoding the node as a one-hot real-valued vector. This representation preserves the basic characteristics of each student node while avoiding an overly complex parameterization. One-hot encoding, a commonly employed method for representing discrete variables, is utilized such that the identity of a student node is indicated by a "1" in one element of the vector and "0" in all others. The resulting initial state embedding is denoted as $g_u^{(0)}$, which represents the initial feature information of student node n_u in the graph. In this manner, the fundamental characteristics of each student node are clearly captured, thereby providing a basis for subsequent computations by the convolutional neural network (CNN).

Traditional CNNs are primarily applied to image data, where convolutional operations extract local information from specific regions of an image via a local receptive field. In the context of graph-structured data, the convolutional operation must be suitably adapted to effectively propagate information. To this end, the convolutional operation was redefined from the perspective of relational structure, thereby extending its application to graph data. Specifically, the model considers three distinct types of mobile interaction relationships among students: mobile interaction relationships L_D, communication interactions L_Z, and attribute association subgraphs L_X. Since these relationship types play different roles during the convolutional propagation process, they are handled separately in the convolutional computation. The embedding representation of a student node is updated through message propagation from neighboring student nodes and their respective relationship types, while the convolutional operation is implemented by applying weighted computations to the different types of adjacency matrices. This approach ensures that the influence of each relationship type on the representation of student nodes is fully accounted for. Let g_u^m denote the hidden state of student node u at the m-th layer, with the dimensionality at layer m represented by $f^{(m)}$. The neighboring student nodes of node u are denoted by $V(u)$. The activation function used for message passing between the model layers is represented by $\delta(\cdot)$, and the neural network function, or a simple linear transformation function, is denoted by $L(\cdot)$. The specific formulation of the local convolutional operation is given by:

$$g_u^{(m+1)} = \delta\left(\sum\nolimits_{k \in Vu} L^{(m)}\left(g_u^{(m)}, g_k^{(m)}\right)\right) \tag{2}$$

The initial embedding representation of a student node n_u is defined as $g_u^{(0)}$, and it can be expressed as follows:

$$g_u^{(0)} = [a_1, a_2, \ldots, a_v] \tag{3}$$

In GCN, the embedding representation of a student node is propagated through the embedding representations of its neighboring student nodes. At each layer of the model, the embedding representation g_u^m of student node n_u is obtained by a weighted combination of its previous layer embedding representation g_u^{m-1} and the embedding representations of directly connected neighboring student nodes. This process is implemented using matrix multiplication between the adjacency matrix and the learnable parameter matrix. During training, the adjacency matrix captures the connectivity relationships among student nodes in the graph, while the learnable parameter matrix is obtained through training to determine the relative importance of each student node with respect to its neighboring nodes. When handling different types of mobile interaction relationships, the model separately processes the adjacency matrices corresponding to each type of relationship, ensuring that the features of each relationship type are accurately incorporated into the embedding representation of student nodes. Let j represent D, Z, and X, where $V_D(\cdot)$ denotes social interaction neighbors, $V_Z(\cdot)$ represents communication interaction neighbors, and $V_X(\cdot)$ denotes attribute association neighbors in the extended social graph, respectively.

$$g_u^{(m+1)} = \delta\left(\sum\nolimits_{j\in\{D,Z,X\}}\sum\nolimits_{k\in V_j}\frac{1}{\left|V_j(u)\right|}\Phi^{(m)}g_k^{(m)} + \Phi_p^{(m)}g_k^{(m)}\right) \tag{4}$$

During the training process, convolutional operations are propagated through matrix multiplication. By multiplying the adjacency matrix with the learnable parameter matrix, the embedding representation of each student node is obtained. This process is iteratively performed in each layer of the convolutional network, gradually updating the representation of student nodes. Different types of interaction relationships are incorporated into the updating process through their respective adjacency matrices, ensuring that the features of each relationship type are independently and effectively learned during training. Through this approach, the model is capable of capturing the global structure of the graph while constructing personalized learning paths at the student node level, thereby enabling the discovery of mobile interaction relationships among students. This propagation mechanism, based on GCN, effectively mitigates overfitting while enhancing the model's capability to process complex graph structures. As a result, the model maintains efficient and accurate learning performance even when dealing with graph-structured data containing multiple edge types. Specifically, if the value at row u, column k of a given adjacency matrix is 1, it indicates the existence of a relationship of the corresponding type between student nodes n_u and n_k. Let I denote the identity matrix, and the adjacency matrix at each layer can be expressed as follows:

$$L^{(m)} = \sum\nolimits_{j\in\{D,Z,X\}}(\Phi^{(m)}L_j) + I \tag{5}$$

The final embedding representation of student nodes in the model, denoted as $G^{(m+1)}$, is given by:

$$G^{(m+1)} = \delta(L^{(m)}G^{(m)}\Phi^{(m)}) \tag{6}$$

3.3 Prediction scoring layer

To enable the effective prediction of hidden relationships among students, a prediction scoring layer was introduced. The primary function of this layer is to assess whether a mobile interaction relationship exists between a given pair of student nodes (n_u,n_k) by leveraging the trained student node embedding representation $C = \{c_0,c_1,\ldots,c_{|N|}\}$. Through multi-layer CNN-based embedding learning, the model obtains the final embedding representation for each student node, encapsulating its multidimensional feature information. In the prediction scoring layer, these embedding representations are utilized as inputs, and the existence of a mobile interaction relationship between student node pairs is determined by computing their similarity or association. Specifically, for each student node pair (n_u,n_k), a similarity measure (such as cosine similarity or dot product) is employed to compute a corresponding score, which is then used to predict the presence of an interaction relationship.

Let o_{uk} denote the probability of a link existing between the student node pair (n_u,n_k). The scoring function is defined as follows:

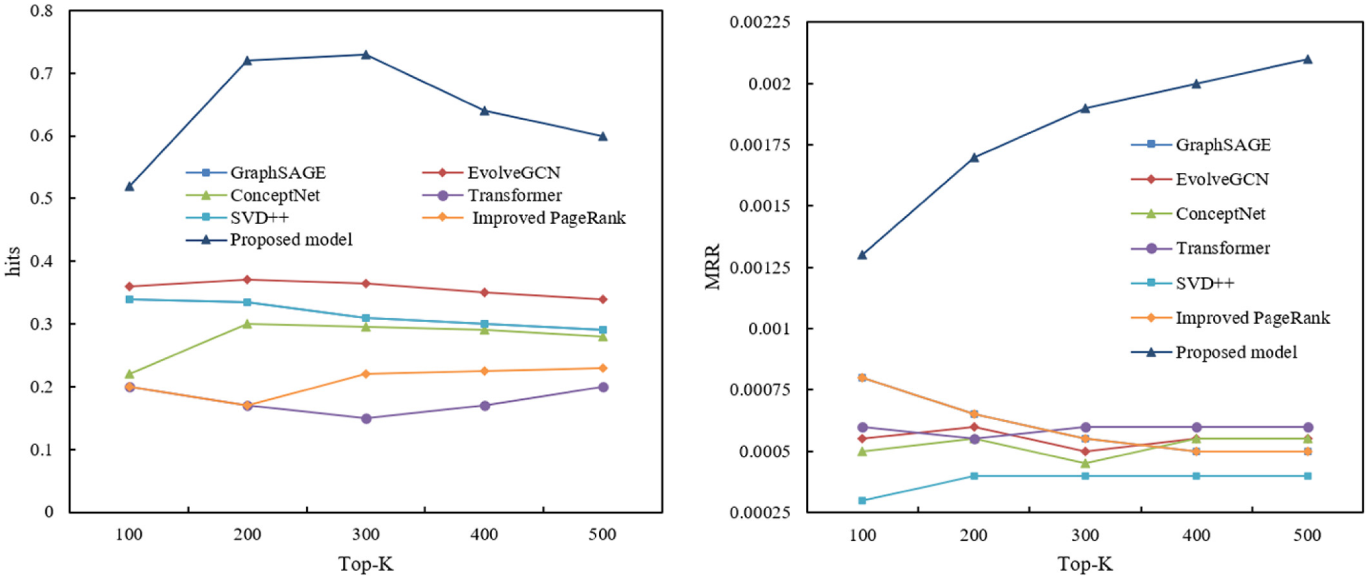
$$o_{uk} = \sum\nolimits_{j\in\{D,Z,X\}} c_u^S F_j c_k \tag{7}$$

During the training process, the model employs a semi-supervised graph auto-encoder approach, meaning that the model is trained not only with actual student mobile interaction relationships but also with a randomly selected set of negative samples. This strategy enhances the model's ability to distinguish between student node pairs that share a relationship and those that do not. Initially, CNN is used to learn from the three different types of relationships. During the decoding process, the influence of these relationship types is integrated and analyzed to ensure that the characteristics of each relationship type are fully utilized. Subsequently, in the prediction scoring layer, the final embedding representation of each student node is fed into the scoring function to compute the predicted score for each student node pair. To optimize the model's predictive performance, cross-entropy was adopted as the objective function in this study. By minimizing the cross-entropy loss, model parameters are adjusted to improve prediction accuracy. Cross-entropy serves as an effective metric to measure the discrepancy between the predicted results and the actual labels, guiding the optimization process throughout training. This ultimately enables the accurate prediction of hidden mobile interaction relationships among students. Let $\Omega(\cdot)$ represent the logistic function. The objective function is defined as follows:

$$M = -\frac{1}{(1+T)\left|R\right|}\sum\nolimits_{(u,k)\in F} b\log\Omega(o_{uk}) + (1-b)\log(1-\Omega(o_{uk})) \tag{8}$$

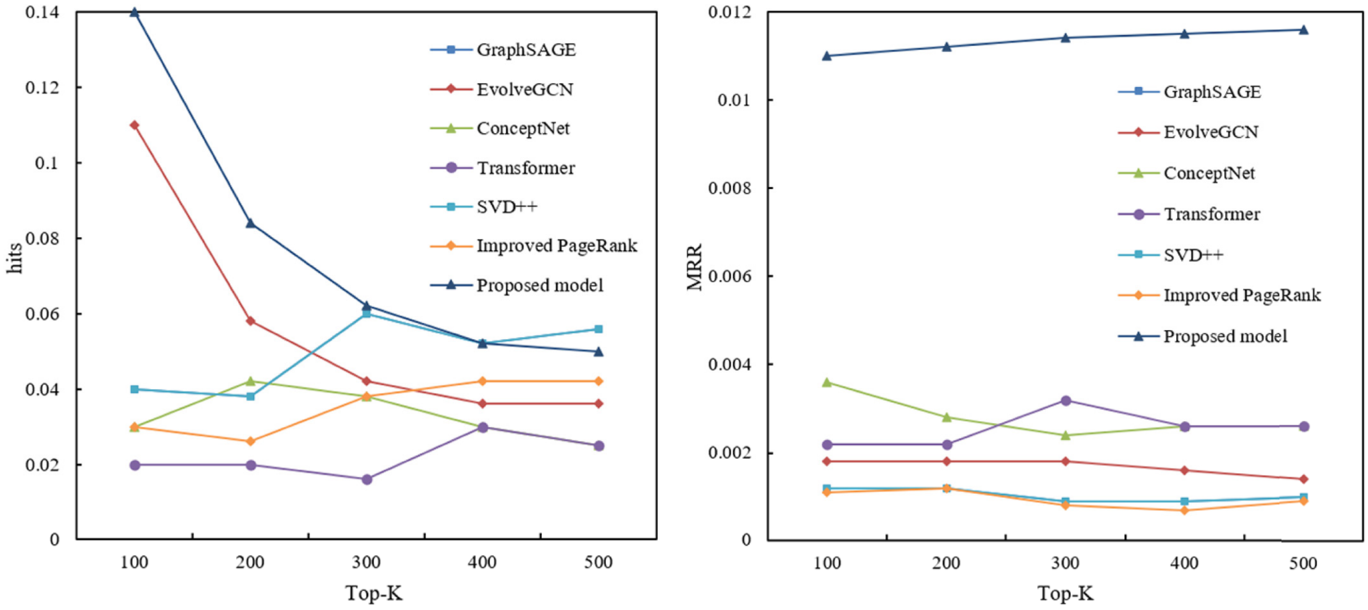
4 EXPERIMENTAL RESULTS AND ANALYSIS

The results of the training and test sets presented in Figures 4 and 5 demonstrate that the proposed model exhibits superior performance across different Top-K values, particularly in terms of the Hits@K and mean reciprocal rank (MRR) evaluation metrics. On the training set, the performance of the proposed model significantly outperforms other baseline models. Specifically, at Top-100 and Top-200, the Hits@K values reach 0.52 and 0.72, respectively, which are considerably higher than those of graph sample and aggregate (GraphSAGE) (0.34 and 0.335), evolving graph convolutional network (EvolveGCN) (0.36 and 0.37), and singular value decomposition (SVD)++ (0.34 and 0.335). In terms of MRR, the proposed model also demonstrates outstanding performance, achieving 0.0013 at Top-100 and 0.0017 at Top-200. In contrast, GraphSAGE attains only 0.0008 and 0.00065, while SVD++ records even lower values of 0.0003 and 0.0004. Similar trends are observed in the test set, where the proposed model maintains a significant advantage in Hits@K and MRR. Notably, at Top-100, the model achieves a Hits@K of 0.14 and an MRR of 0.011, both of which are markedly higher than those of competing models such as GraphSAGE and EvolveGCN. The superior performance of the proposed model in the MRR metric on the test dataset further highlights its stability and generalization capability. Based on these experimental findings, the conclusions can be drawn below. The proposed model demonstrates a strong ability to capture and predict student interaction patterns, significantly outperforming traditional algorithms in discovering mobile interaction relationships among students. The results indicate that the personalized learning path model proposed in this study provides a more accurate representation of dynamic student interactions during the learning process, thereby offering robust support for enhancing academic achievement.



a) Hits **b) MRR**

Fig. 4. Discovery results of student mobile interaction relationships in the training set



a) Hits **b) MRR**

Fig. 5. Discovery results of student mobile interaction relationships in the test set

Based on the analysis presented in Table 1, student personalized attributes exhibit a significant impact on both interaction quality and learning efficiency during the learning process. Specifically, individual characteristics such as personality traits, emotional expressiveness, learning ability, and self-perception influence interaction quality and learning efficiency to varying degrees. Regarding interaction quality, significant differences are observed in personality traits (*t* = 2.524, *p* = 0.011), emotional expressiveness (*t* = 2.896, *p* = 0.003), learning ability (*t* = –2.785, *p* = 0.003), and self-perception (*t* = –3.425, *p* = 0.001). Among these factors, emotional expressiveness and self-perception show particularly strong associations with interaction quality. Similarly, the richness of communication content (*t* = 3.412, *p* = 0.001), clarity of language expression (*t* = 2.162, *p* = 0.036), and the strength of emotional tone (*t* = 2.136, *p* = 0.026) also exhibit significant effects on interaction quality. Notably, openness of communication demonstrates an extremely significant difference (*t* = –3.569, *p* = 0.000). These findings indicate that student personalized attributes play a critical role in determining the quality of interactions and learning efficiency, ultimately influencing academic achievement.

Table 1. Difference analysis of factors influencing student mobile interaction relationships in personalized learning paths

	Influencing Factor	Impact Aspect	*M*	*SD*	*t*	*p*
Student personalized attributes	Personality traits	Interaction quality	0.036	0.025	2.524	0.011**
		Learning efficiency	0.028	0.021		
	Emotional expressiveness	Interaction quality	0.062	0.051	2.896	0.003**
		Learning efficiency	0.051	0.031		
	Learning ability	Interaction quality	0.225	0.425	–2.785	0.003**
		Learning efficiency	0.348	0.426		
	Self-perception	Interaction quality	0.356	0.589	–3.425	0.001**
		Learning efficiency	0.569	0.623		
Student communication interaction	Richness of communication content	Interaction quality	0.112	0.091	3.412	0.001**
		Learning efficiency	0.092	0.067		
	Clarity of language expression	Interaction quality	0.124	0.091	2.162	0.036*
		Learning efficiency	0.126	0.071		
	Strength of emotional tone	Interaction quality	0.328	0.227	2.136	0.026*
		Learning efficiency	0.287	0.168		
	Openness of communication	Interaction quality	0.215	0.126	–3.569	0.000**
		Learning efficiency	0.265	0.224		

Notes: *indicates significant at the 0.05 level, and **indicates significant at the 0.01 level.

The cluster analysis results in Table 2 indicate that personalized learning paths of students are closely associated with their academic achievement enhancement. Significant differences are observed among clusters in terms of study time investment, interaction frequency, and interaction quality. For instance, students in Cluster 1 exhibit higher study time investment (32.26), interaction quality (53.59), and task completion rate (55.36) compared to other clusters, indicating that these factors contribute positively to academic achievement enhancement. In contrast, students in Cluster 6 show lower values for these metrics, with study time investment and interaction quality at 12.36 and 43.26, respectively, suggesting weaker academic performance. Additionally, students in Cluster 1 demonstrate significantly higher social interaction frequency (92.35) and self-efficacy (63) compared to other clusters, highlighting the positive impact of social engagement and self-efficacy on learning outcomes. Conversely, students in Cluster 5 experience lower perceived academic pressure (67.54) but also exhibit relatively lower learning feedback response speed and collaborative learning frequency, suggesting that their academic achievement enhancement may be constrained compared to other groups.

Table 2. Cluster analysis of student mobile interaction behavior prediction and academic achievement enhancement in personalized learning paths

Variable	Cluster					
	1	2	3	4	5	6
Study time investment	32.26	28.26	26.35	17.56	12.36	12.36
Interaction frequency	21.36	13.65	16.85	13.26	15.64	12.48
Interaction quality	53.59	46.85	35.62	28.62	22.85	43.26
Diversity of learning content	17.25	22.31	18.51	12.36	22.36	14.69
Learning feedback response speed	32.02	17.89	26.45	17.52	15.69	23.51
Collaborative learning frequency	11.56	22.36	11.23	13.52	11.34	8.95
Task completion rate	55.36	14.20	35.69	42.31	17.59	18.62
Post-class learning continuity	15.69	16.35	17.26	5.69	8.12	5.98
Learning strategy usage frequency	25.61	14.26	37.69	35.26	23.69	8.36
Perceived academic pressure	84.23	92.36	72.63	81.23	67.54	62.54
Social interaction frequency	92.35	82.36	87.26	73.23	62.36	64.23
Self-efficacy	63	74	5	62	3	45

Table 3. Correlation analysis of student mobile interaction and academic achievement enhancement in personalized learning paths

	Knowledge	Skills	Engagement	Self-Efficacy	Overall Academic Achievement
Instant messaging	0.612**	0.378**	0.512**	0.412**	0.512**
Online discussion	0.389**	0.285**	0.313**	0.418**	0.413**
Collaborative document editing	0.374**	0.379*	0.316**	0.278**	0.418**
Video conferencing	0.312**	0.236*	0.268*	0.435**	0.356**
Group collaborative learning	0.625**	0.354**	0.526**	0.346**	0.457**
Online Q&A	0.618**	0.356**	0.518**	0.348**	0.446**
Social media interaction	0.523**	0.289**	0.379**	0.389**	0.426**

The correlation analysis results in Table 3 indicate a significant positive relationship between personalized learning paths supported by mobile technology and student academic achievement enhancement. Strong correlations are observed between various interaction methods and students' knowledge, skills, engagement, self-efficacy, and overall academic achievement. Specifically, instant messaging exhibits a correlation coefficient of 0.512 ($p < 0.01$) with overall academic achievement, highlighting its positive influence. Similarly, group collaborative learning shows a significant impact, with a correlation coefficient of 0.457 ($p < 0.01$). Additionally, online Q&A ($r = 0.446$, $p < 0.01$) and social media interaction ($r = 0.426$, $p < 0.01$) also demonstrate strong positive correlations with academic achievement. These findings suggest that student interactions through mobile technology platforms, such as online discussions, collaborative document editing, and video conferencing, contribute to varying degrees of knowledge acquisition and skill development, ultimately enhancing academic achievement.

From these correlation analyses, it can be inferred that personalized learning paths supported by mobile technology effectively promote academic achievement enhancement through multiple interaction methods. Forms of interaction such as instant messaging and group collaborative learning not only improve knowledge retention and skill development but also enhance student engagement and self-efficacy. In particular, instant messaging and online Q&A significantly increase interaction frequency and feedback quality during the learning process, further contributing to academic achievement. In addition, through social media interactions and other means, students can collaborate and communicate more effectively across time and space. This flexible learning approach provides students with more learning opportunities and helps them overcome the limitations of traditional learning paths.

5 CONCLUSION

Through an in-depth analysis of student mobile interaction relationships in personalized learning paths, this study reveals the significant role of personalized learning in enhancing academic achievement. First, by examining student interaction patterns within personalized learning paths, various interaction methods—including instant messaging, group collaborative learning, and online Q&A—were identified as having a positive impact on the learning process. The findings confirm the critical role of personalized student characteristics and interaction behaviors in determining learning outcomes. Additionally, through the construction of an extended mobile interaction graph, this study further demonstrates how mobile technology facilitates more effective student interactions, ultimately contributing to academic achievement improvement. The results indicate that active participation in interaction quality, collaboration frequency, and emotional expressiveness is significantly positively correlated with academic achievement. Especially in terms of interaction frequency and task completion rate, personalized learning paths significantly improve students' overall academic performance. Therefore, when designing personalized learning paths, educators can maximize students' learning potential by aligning their designs with students' personalized needs and interaction characteristics.

However, this study has certain limitations. First, the sample size in this study is relatively limited and primarily focused on specific disciplines and educational stages. Future research could expand the sample scope to include a broader range of subjects and students of varying age groups, ensuring the generalizability of the findings. Second, although mobile interaction behaviors and academic achievement were extensively analyzed, the variations in these interaction patterns across different cultural or educational settings were not fully explored. Future research could consider the influence of these variables on learning effectiveness. Lastly, as mobile technology continues to evolve, the tools and methods used to implement personalized learning paths will also undergo significant advancements. Future studies could explore the integration of emerging technologies, such as artificial intelligence and big data analytics, to further optimize personalized learning path design, thereby optimizing student learning experiences and academic outcomes.

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