

PAPER

Enhancing Students' Self-Regulation and Autonomous Learning in Higher Education through Interactive Mobile Technologies

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ABSTRACT

With the rapid advancement of information technology, the application of interactive mobile technologies in higher education has garnered increasing attention, particularly for their potential in enhancing students' self-regulation and autonomous learning capabilities. Traditional instructional models often rely on fixed classroom settings and predetermined teaching schedules, making it difficult to adapt to individual differences and diverse learning needs. In contrast, interactive mobile technologies offer personalized learning resources and real-time feedback, thereby improving the flexibility and efficiency of self-directed learning. As a result, exploring how to leverage these technologies to foster students' self-regulation and autonomy has become a critical issue in the field of educational technology. Existing studies primarily focus on the cultivation of autonomous learning and self-regulation, as well as the design of personalized learning path recommendation systems. However, many of these systems are based on static data and fail to adapt in real time to the dynamic changes in students' learning behaviors, limiting their practical effectiveness in educational settings. Therefore, a pressing challenge is to develop a system that can dynamically adjust learning paths in response to changes in student behavior and learning needs. This study proposes a dynamic personalized learning path recommendation model based on latent association information and dynamic graph neural networks. By conducting real-time analysis of student learning behaviors and continuously updating the model, the system aims to construct more intelligent and individualized learning paths. This, in turn, enhances students' self-regulation and autonomous learning abilities. The findings provide new technological support for teaching practices in higher education and offer theoretical and methodological contributions to the advancement of personalized education.

KEYWORDS

interactive mobile technologies, self-regulation, autonomous learning ability, personalized learning path, dynamic graph neural networks

Lu, L. (2025). Enhancing Students' Self-Regulation and Autonomous Learning in Higher Education through Interactive Mobile Technologies. *International Journal of Interactive Mobile Technologies (iJIM)*, 19(13), pp. 19–32. <https://doi.org/10.3991/ijim.v19i13.56595>

Article submitted 2025-02-03. Revision uploaded 2025-04-25. Final acceptance 2025-05-13.

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1 INTRODUCTION

With the rapid development of information technology, especially the popularization of mobile internet technology and smart devices, the teaching models and learning methods in higher education are undergoing profound changes [1–3]. Traditional teaching methods often rely on fixed classroom time and location [4, 5], and the learning progress and content are often unable to be flexibly adjusted according to students' individualized needs [6]. However, the application of interactive mobile technology provides students with more flexible learning methods [7], enabling learning activities to take place at any time and in any location [8, 9]. These technologies not only provide students with rich learning resources and real-time learning support but also promote the improvement of autonomous learning and self-management ability. How to use interactive mobile technology to help students improve their self-management and autonomous learning ability has become an important topic in current educational research.

However, most existing research focuses on theoretical discussion or single technology applications [10–12], lacking systematic research on the role of interactive mobile technology in enhancing students' self-management and autonomous learning ability. For example, although many studies have proposed methods for constructing personalized learning paths [13], they often ignore the dynamic changes in the learning process and fail to fully consider the real-time changes in students' behaviors and needs. In addition, traditional personalized recommendation algorithms often conduct analysis based on static data [14–18], making it difficult to respond to the complex changes and dynamic needs in students' learning processes, which greatly reduces the effectiveness of the recommendation system in practical applications. Therefore, current research methods have certain limitations and shortcomings in the process of enhancing students' self-management and autonomous learning ability.

This study mainly focuses on two aspects: first, the definition of the dynamic personalized learning path recommendation problem oriented to the improvement of students' self-management and autonomous learning ability; second, the design of a dynamic personalized learning path recommendation model based on latent association information and dynamic graph neural networks. Through the dynamic analysis of students' learning behaviors and needs, a more intelligent and flexible personalized recommendation system is constructed, thereby improving students' self-management ability and autonomous learning ability. This study not only provides a new research perspective for the field of educational technology but also provides effective technical support for teaching practice in higher education and has important theoretical and practical value.

2 PERSONALIZED LEARNING PATH RECOMMENDATION PROBLEM

In the process of mobile learning, students' learning needs and behaviors dynamically adjust with changes in time and context. Traditional static learning path recommendation systems are difficult to timely capture and adapt to these changes. Dynamic graph neural networks can dynamically update learning path recommendations based on students' real-time behavior data and learning status in the interactive mobile learning network. Through continuous observation and analysis of students' learning processes, dynamic graph neural networks can discover

potential learning patterns and associated information in the learning process. These pieces of information can be used to precisely adjust personalized recommendations to meet students' different needs at different learning stages, helping them better manage their learning process and improve their autonomous learning ability. Figure 1 shows the dynamic change diagram of personalized mobile interactive learning.

The design of a dynamic personalized learning path recommendation system is not only an optimization of students' learning paths but also aims to guide students to actively carry out self-management in the learning process. Self-management ability is crucial for students' autonomous learning. It includes multiple aspects such as time management, goal setting, and resource planning. Through interactive mobile technology, students can learn at any time and in any place. In this process, dynamic graph neural networks can capture students' learning behaviors and emotional responses in real time and dynamically recommend suitable learning resources and activities for students. Through this kind of real-time personalized recommendation system, students can obtain timely support and guidance according to their learning progress and difficulties, thereby improving their self-management ability and promoting more initiative in their learning.

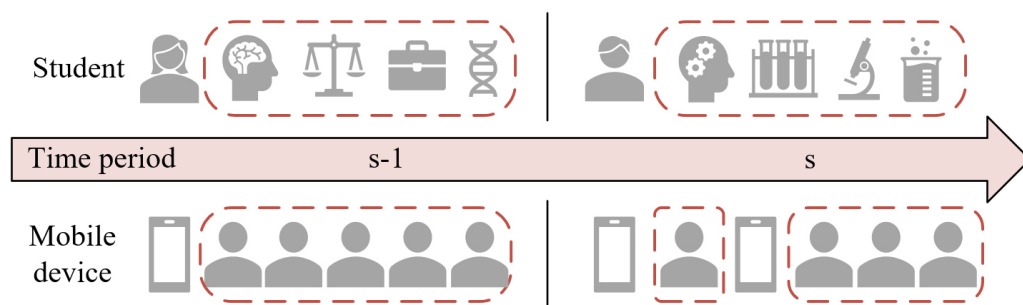


Fig. 1. Dynamic change diagram of personalized mobile interactive learning

In this study, the student set is defined as $I = \{i_1, i_2, \dots, i_v\}$, and the learning resource set is defined as $N = \{n_1, n_2, \dots, n_L\}$, where V is the number of students and L is the number of learning resources. E is the relational matrix of interactions between students and learning resources. D denotes the relationship matrix of students' trusted friends. Z is the relationship matrix of students' potential associated students. For the interaction matrix E , e_{uk} represents the rating value of student u for learning resource k . If student u has not rated learning resource k or the interaction is unknown, then $e_{uk} = 0$. For the trust matrix D , if student u trusts learning resource k , then $d_{uk} = 1$, otherwise 0. For the potential association relationship matrix Z , if student u has similar interaction behaviors with learning resource k , then $z_{uk} = 1$, otherwise 0. Similarly, there is also similarity among learning resources. Matrix F represents the similarity relationship between learning resources. Define $H_I = (I, R_I)$ as the interactive mobile learning network graph of students, where R_I is the edge set of relationships connecting students; $H_N = (N, R_N)$ is the learning resource correlation graph, where R_N connects similar learning resources.

The trusted friends set of student i_u is denoted as V_u^{ii} , where the superscript "ii" indicates an undirected edge between two trusted students. The potential associated students set of student i_u is denoted as V_u^{izi} , where the superscript "izi" indicates an undirected edge between two potential associated students. V_u^{in} denotes the set of learning resources that student i_u has interacted with, where the superscript "in"

indicates a directed edge from student to learning resource (rating). The set of learning resources similar to learning resource n_k is denoted as, where the superscript “ nn ” indicates an undirected edge between similar learning resources. V_k^{ni} denotes the set of students who have interacted with learning resource n_k , where the superscript “ ni ” indicates a directed edge from resource to student (being rated).

For student i_u , each of his interactions can be represented as a quadruple (n_k, e_{uk}, g, s) , where n_k indicates that student u is learning resource k , e_{uk} indicates the rating by student u on resource k , g indicates the reliability of the rating, and s is the timestamp. Denote S_u^n as the sequence of all timestamps of student i_u 's learning activities sorted in ascending order by time; then the set of learning resources learned by student i_u is $T_u^n = Hn_{k \in G} G_{p \in S_u^n}$. Similarly, for learning resource n_k , each of its interactions can be represented as a quadruple (i_u, e_{uk}, g, s) , where i_u represents student u who learns resource k , e_{uk} is the rating value, g the reliability, and s the timestamp. Let S_k^i be the ascending timestamp sequence of students learning resource n_k , then the corresponding student sequence can be written as $T_k^i = Hn_{k \in G} G_{p \in S_k^i}$.

The interactive mobile learning network recommendation problem can be defined as: given the observed student-learning resource interaction matrix E , the interactive mobile learning network graph H_p , and the learning resource relationship graph H_{N^p} , predict the unknown interactions in matrix E , i.e., the future ratings of student iu on learning resource n_k that have not been observed.

Considering that most datasets do not explicitly provide prior association information among learning resources, we use cosine similarity to measure the similarity between learning resources. Specifically, for each learning resource n_k , the k -th column of interaction matrix E records the interaction ratings between this resource and all students. By computing the cosine similarity of the interaction rating vectors between learning resources, we can obtain the similarity between learning resources n_k and n_j . Next, based on the computed similarity values, we extract the top- k most similar learning resources for each learning resource as its related neighbors. These similar learning resources help construct the learning resource correlation graph H_{N^p} , which is used to capture the relationships between resources before resource embedding, providing important support for the dynamic personalized learning path recommendation.

$$SIM(k, j) = \frac{E(k)^T E(j)}{\|E(k)\|_2 \|E(j)\|_2} \quad (1)$$

In the process of computing the potential associated students, in addition to rating data, we also need to consider the interaction details between students and learning resources. Specifically, in order to calculate the similarity between students, we only consider the number of commonly interacted learning resources. The more learning resources two students have in common, the more similar their learning interests are, and hence, the higher their similarity. To improve computational efficiency, a threshold is set in this paper: if the number of commonly interacted learning resources between two students is less than 5, they will not be considered as potential associated students. In this way, we can reduce the computational cost and ensure the model focuses on student pairs with significant similarity. According to the similarity values between students, we extract the top- k most similar potential associated students for each student to construct the student-related graph H_r . Taking students i_k and i_j as an example:

$$SIM(k, j) = COUNT(V_k^{in} \cap V_j^{in}) \quad (2)$$

3 DYNAMIC PERSONALIZED LEARNING PATH MODEL WITH ASSOCIATION INFO AND GNNS

3.1 Embedding of students and learning resources

In the model, the embedding of students and learning resources is one of the core components. Each student is represented by an embedding vector o_u , which reflects the personalized characteristics of the student in the learning network, indicating their learning behavior and interest. Each learning resource is represented by an embedding vector w_k , which captures the content characteristics of the learning resource and its relationship with students' learning behaviors. To model the interactions between students and learning resources, the rating e_{uk} that a student gives to a learning resource is embedded into an f -dimensional vector, denoted as r_{uk} . This embedding approach allows each rating to be not just a discrete value but a high-dimensional continuous vector that captures fine-grained features of the rating and deeper interaction information between students and resources.

The embedding vectors o_u and w_k of each student and learning resource in the model are learned and updated through the graph neural network. For student i_k and learning resource n_k , their embedding vectors o_u and w_k are optimized through the message-passing mechanism of the graph neural network. Specifically, during model training, the embedding's of students and learning resources are dynamically adjusted based on students' ratings of learning resources and other potential association information. In this embedding learning process, the reliability of the rating e_{uk} is also considered, and the impact of the rating is adjusted by the parameter g_{uk} . The higher the credibility of the rating, the greater its contribution to embedding updates, thus more accurately capturing the actual interaction relationship between students and learning resources. Suppose the interaction embedding from n_k to i_u is represented by $a_{u \leftarrow k}$ and the interaction embedding from i_u to n_k is represented by $b_{k \leftarrow u}$. The concatenation operation of the two vectors is represented by \oplus , and the two-layer perceptron's are represented by h^{in} and h^{ni} . Then, the interaction embedding representation between student i_u and learning resource n_k can be calculated by the following formula:

$$a_{u \leftarrow k} = h^{in}([r_{uk} \oplus w_k]), b_{k \leftarrow u} = h^{in}([r_{uk} \oplus o_u]) \tag{3}$$

In the interaction between students and their trusted friends, since the trust relationship itself is a relatively stable and direct connection, we consider that such interactions have little influence on the reliability of ratings. Therefore, there is no need to consider the credibility of ratings in this type of interaction. Suppose the superscript i of a indicates the student, whose trusted friends are represented by ii , and the two-layer perceptron's are represented by h_1^{ii} and h_2^{in} . Then, the calculation formula is:

$$a_{u \leftarrow k}^i = h_1^{ii}([r_{uk} \oplus w_k]), a_{u \leftarrow k}^{ii} = h_2^{in}([r_{ukj} \oplus w_k]) \tag{4}$$

In the interaction between students and potential associated students, since the trust relationship between these students is relatively weak and the rating data comes from unfamiliar students, more attention needs to be paid to the credibility of ratings. In order to better model the influence of potential associated students, the model processes the interaction between students and potential associated students and the learning resources' ratings on students in the order of similar learning

resources. Suppose the three-layer perceptron's are represented by h_3^{in} , h_1^{in} , and h_2^{in} , and the reliability of the rating e_{uk} is represented by g_{uk} , then the calculation formulas are:

$$\begin{aligned}
 a_{u \leftarrow k}^{zi} &= h_3^{in} \left([r_{uk} \oplus g_{uk} \oplus w_k] \right), \\
 b_{k \leftarrow u}^u &= h_1^{ni} \left([r_{uk} \oplus g_{uk} \oplus o_u] \right), \\
 b_{k \leftarrow u}^{uu} &= h_2^{ni} \left([r_{uk} \oplus g_{uk} \oplus o_u] \right)
 \end{aligned}
 \tag{5}$$

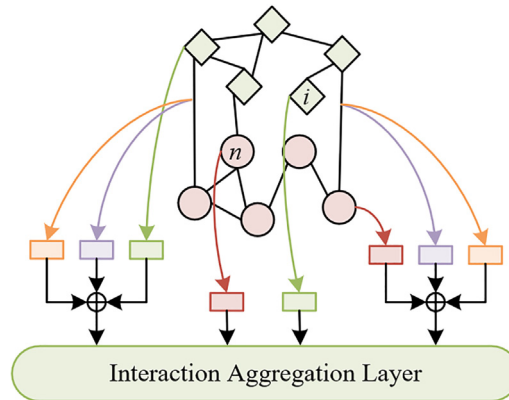


Fig. 2. Model embedding layer structure diagram

Figure 2 shows the model embedding layer structure diagram. By continuously optimizing the embedding vectors of students and learning resources, the model can adjust learning path recommendations in real time, helping students better manage their learning process. During the model running process, changes in students' learning progress and needs will directly affect the update of embedding vectors, thereby realizing dynamic and personalized learning resource recommendations.

3.2 Interaction information aggregation layer

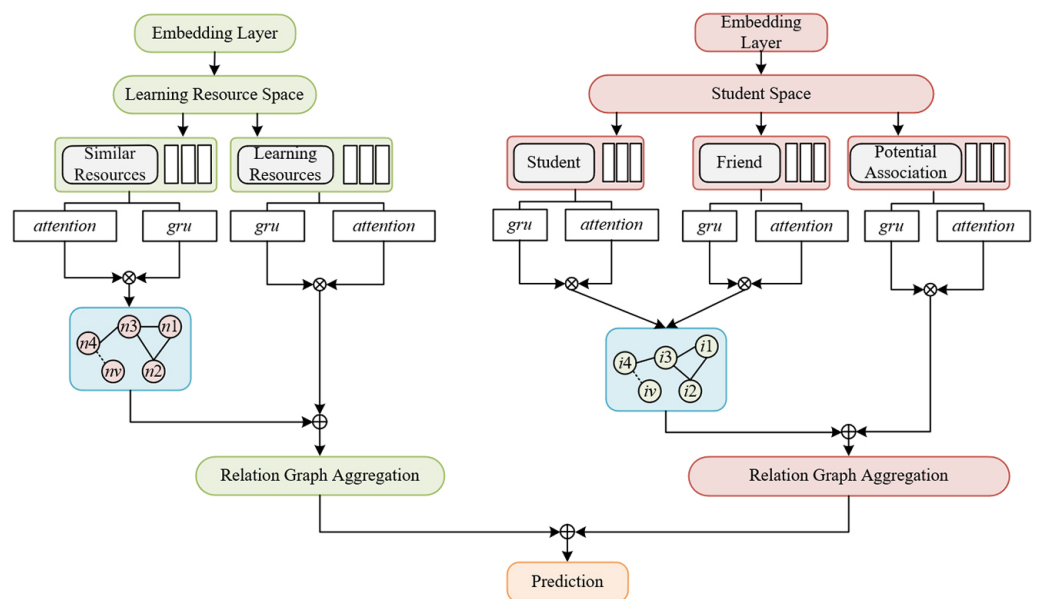


Fig. 3. Model interaction information aggregation layer and relationship graph aggregation layer structure diagram

Figure 3 shows the model interaction information aggregation layer and relationship graph aggregation layer structure diagram. The interaction information aggregation layer is responsible for processing the interaction data between students and learning resources and converting this information into useful representations. In order to effectively capture the dynamic preferences of students and the attractiveness of learning resources, the interaction information aggregation layer needs to consider both short-term dynamics and long-term static interests and attractiveness.

1. For short-term dynamic representation, the interaction information aggregation layer uses GRU to model the interaction sequence between students and learning resources. GRU can capture the changes in students' short-term interests when processing sequential data, such as a student's increased or decreased interest in a particular learning resource at a certain moment. The interaction sequences $A(u)$ and $B(k)$ between student i_u and learning resource n_k are processed by the GRU network, thereby obtaining the short-term dynamic representations of student and learning resource preferences. Assuming the dynamic representations of student preference and learning resource attractiveness are represented by g_u^t and g_k^t respectively, the specific calculation formula is:

$$g_u^t = GRU(A(u)), g_k^t = GRU(B(k)) \tag{6}$$

GRU can dynamically adjust the representations of students and resources in each interaction by effectively modeling sequential data so as to better reflect students' current learning interests. By only taking the last hidden layer output of the GRU, the short-term preferences of students and resources can be effectively extracted, which is crucial for personalized learning path recommendation. In addition, to control computational cost, longer time sequences will be truncated to a fixed length to avoid excessive computational complexity.

2. For long-term static representation, the interaction information aggregation layer uses graph attention network (GAT) to process the long-term relationships between students and learning resources. Each interaction between a student and a learning resource can be regarded as an edge in the student-learning resource graph, which connects the student and the learning resource and contains the interaction information between them. Through the self-attention mechanism in GAT, the model can learn the relative importance of each edge in multiple interaction relationships so as to more accurately capture the long-term static attraction between students and learning resources. Specifically, GAT calculates the attention weights of each relation edge and aggregates the features of multiple edges into the long-term representation of the student or the learning resource. The attention mechanism can effectively focus on important interactions and ignore irrelevant ones, thereby improving the model's representation ability and efficiency. The embedding's $a_{u \leftarrow k}$ or $b_{k \leftarrow u}$ can be regarded as the edge embedding representations in the student-learning resource graph. Suppose the long-term static interest representation of the target student is represented by g_u^M , and the long-term static attraction representation of the learning resource is represented by g_k^M . The nonlinear activation function is represented by δ , and the weights and bias terms of the network are represented by Q_0 and y_0 .

$$\begin{aligned} g_u^M &= \delta \left(Q_0^{in} \sum_{k \in V_u^{in}} \beta_{uk} a_{u \leftarrow k} + y_0^{in} \right), \\ g_k^M &= \delta \left(Q_0^{ni} \sum_{k \in V_u^{ni}} \beta_{uk} b_{k \leftarrow u} + y_0^{ni} \right) \end{aligned} \tag{7}$$

Different from the self-attention mechanism in GAT that ignore the edge features, β_{uk} and β_{ku} represent the attention propagation weights learned on the central node representations (o_u, w_k) and the edge representations ($a_{u \leftarrow k}, b_{k \leftarrow u}$). Specifically, taking β_{uk} as an example, suppose the weights and biases of the first and second layers of the self-attention network are represented by (Q_1, y_1) and (Q_2, y_2) , respectively, the corresponding calculation formula is:

$$\beta_{uk} = \frac{\exp(Q_2^{in} \cdot \delta(Q_1^{in} \cdot [ou \oplus a_{u \leftarrow k}] + y_1^{in}) + y_2^{in})}{\sum_{k \in V_u^{in}} \exp(Q_2^{in} \cdot \delta(Q_1^{in} \cdot [ou \oplus a_{u \leftarrow k}] + y_1^{in}) + y_2^{in})} \quad (8)$$

The long-term static information aggregation formula is written as:

$$\begin{aligned} g_u^M &= AG_{in}(o_u, \{a_{u \leftarrow k}, k \in V_u^{in}\}), \\ g_k^M &= AG_{in}(w_k, \{b_{k \leftarrow u}, u \in V_k^{in}\}) \end{aligned} \quad (9)$$

Combining short-term dynamic representations and long-term static representations is a key step of the model. Through the Hadamard product, the representations of short-term dynamic preferences and long-term static attractions are directly combined to obtain the overall preference representation of the student and the overall attraction representation of the learning resource. This combination method enables the model to consider both students' short-term interest changes and long-term learning preferences, thus achieving more accurate learning path recommendations. In addition, in the context of an interactive mobile learning network, the interactions between students and their trusted friends or potential associated students, as well as the relationships between learning resources and similar learning resources, will also be represented through a similar method. For the preference and attraction representations of trusted friends and potential associated students, the model also obtains the association information between students and learning resources and between students and students through the aforementioned aggregation methods of short-term dynamic and long-term static representations and further enhances the personalization and flexibility of the recommendation system.

3.3 Relation graph aggregation layer

The core principle of the relation graph aggregation layer is to model the complex relationships between students and learning resources through the interactive mobile learning network so as to achieve more accurate personalized learning path recommendations. In the aggregation of student information in the interactive mobile learning network, the interactions between students are not static but dynamically change with time and relationship strength. Through the attention mechanism of the relation graph in the interactive mobile learning network, the model can effectively aggregate the interaction information between students, especially when students are in a strong relationship network their interests and preferences will be more consistent. The attention mechanism assigns different weights to relationships between different students so that strong relationships contribute more to the modeling of students' latent factors, while the influence of weak relationships is relatively small. Suppose the relationship aggregation results of the target student in

the trusted friend network graph and the potential association network graph are represented by g_u^V and g_u^{ZN} respectively, then:

$$\begin{aligned} g_u^V &= AG_{ii} \left(o_u, \{g_p^U, p \in V_u^{ii}\} \right), \\ g_u^{ZN} &= AG_{izi} \left(o_u, \{g_{zp}^U, zp \in V_u^{izi}\} \right) \end{aligned} \tag{10}$$

In the aggregation of related information of learning resources, the model further enriches the latent factors of each learning resource through the association relationships between learning resources. Since there may be similarities or correlations between learning resources, the recommendation of learning resources does not only rely on a single resource but needs to consider the attraction of other related or similar resources to students. Through the graph neural network, the model can aggregate information in the relation graph of learning resources and pass the information of these associated learning resources to the target resource, thereby optimizing the latent factor representation of learning resources. Suppose the relationship aggregation result of the target learning resource in the learning resource relation graph is represented by g_k^V , then:

$$g_k^V = AG_{nn} \left(w_k, \{g_j^X, j \in V_k^{nn}\} \right) \tag{11}$$

3.4 Model output layer

The design of the model output layer relies on two types of information: interaction-based representation and relation-based representation. The interaction-based representation mainly models students' short-term dynamic interests and the attraction of resources through the interaction records between students and learning resources, capturing students' immediate reactions and preference changes toward resources. On the other hand, the relation-based representation further explores long-term interest patterns and similarities by analyzing the potential relationships between students and between resources. In the model output layer, the interaction relationship between students and resources is combined with their potential long-term relationships to obtain the final rating prediction of students for resources. Specifically, suppose the multi-layer perceptron is represented by h_i , h_n , and h_{OP} , the latent factor of student i_u is defined as g_u^i , and the latent factor of learning resource n_k is defined as g_k^n . The calculation formula is as follows:

$$\begin{aligned} g_u^i &= h_i \left(\left[g_u^U \oplus g_u^V \oplus g_u^{ZV} \right] \right), \\ g_k^n &= h_n \left(\left[g_k^X \oplus g_k^V \right] \right) \end{aligned} \tag{12}$$

After obtaining the latent factor g_u^i of i_u and the latent factor g_k^n of learning resource n_k , the unknown rating of the target student for the learning resource can be calculated by the following formula:

$$\hat{e}_{uk} = h_{OP} \left(\left[g_k^i \oplus g_k^n \right] \right) \tag{13}$$

In order to optimize the accuracy of the model output, the model uses mean squared error as the loss function to measure the difference between the predicted rating and the actual rating. During the training process, $ML = 1 / 2 | P | \sum_{(u,k)} \in P (\hat{e}_{uk} - e_{uk})$

is used to calculate the loss of the model, where e_{uk} is the real rating and \hat{e}_{uk} is the predicted rating by the model. Through the gradient descent method, the model continuously adjusts its parameters to make the predicted ratings closer to the real ratings, thereby improving the accuracy of the recommendation. To avoid the overfitting problem, the model also uses the dropout technique to improve the generalization ability of the model. The dropout method randomly drops some neurons in the neural network, reducing the model's excessive dependence on training data, ensuring its stable performance on different datasets, and further enhancing the recommendation effect of the model.

4 EXPERIMENTAL RESULTS AND ANALYSIS

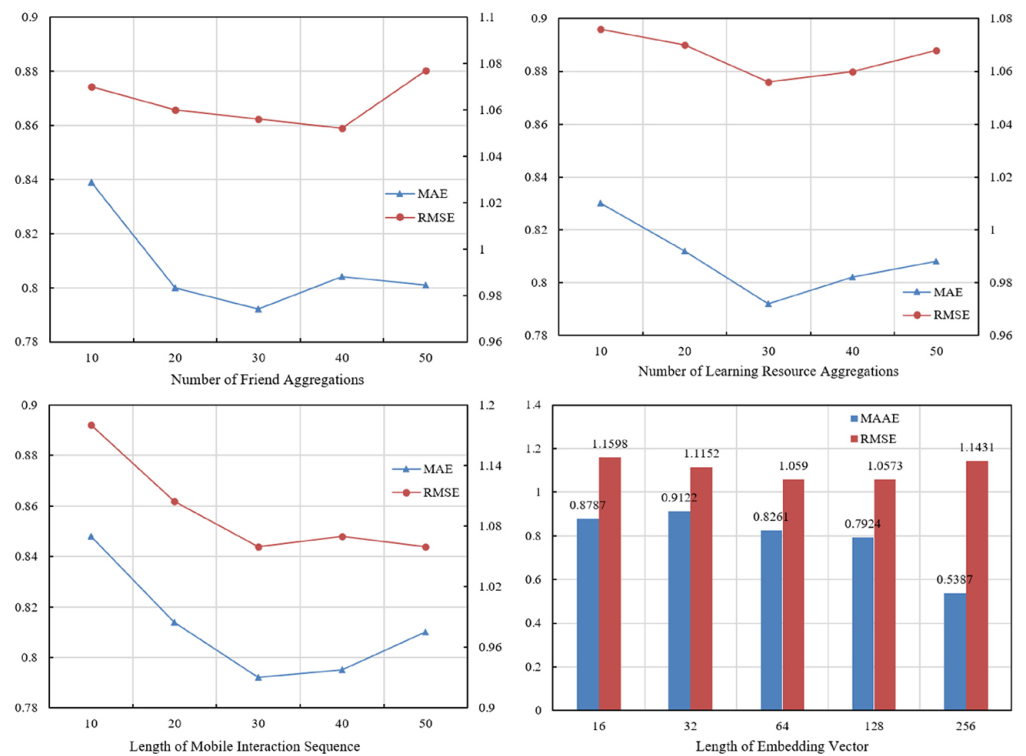


Fig. 4. Parameter sensitivity analysis diagram

According to the experimental results in Figure 4, the sensitivity analysis of the dynamic personalized learning path recommendation model proposed in this paper demonstrates the impact of multiple parameters on the model performance under different aggregation numbers and embedding vector lengths. Firstly, regarding the impact of “number of friend aggregations” and “number of learning resource aggregations,” it can be observed that as the aggregation number increases, MAE and RMSE values show a certain downward trend within a specific range. Especially in the aggregation number interval of 20 to 30, the reduction in MAE and RMSE is the most significant, indicating that an appropriate aggregation number helps optimize the prediction accuracy of the model. However, after exceeding a certain threshold, the effect tends to stabilize and even shows slight fluctuations. Secondly, for the experimental results of the “length of mobile interaction sequence,” with the increase of sequence length, the performance of MAE and RMSE presents a certain degree of fluctuation, particularly at the sequence lengths of 40 and 50, where the

MAE and RMSE values show a certain rise. This indicates that longer sequence lengths may increase the model complexity and training difficulty, thereby affecting the prediction accuracy. Finally, the impact of “embedding vector length” on model performance is particularly significant. Especially when the embedding vector length increases, the MAE and RMSE values decrease significantly. Particularly at the embedding vector length of 128, the MAE achieves the best performance of 0.7924, while the RMSE value approaches the lowest at 1.0573. This result indicates that higher-dimensional embedding vectors help capture the details of students' personalized learning needs, thereby improving the prediction ability of the model.

According to the rating prediction comparison results in Table 1, the model proposed in this paper shows certain advantages in performance on both the training set and testing set compared to other models. Firstly, on the training set, the RMSE of this model is 0.9425 and the MAE is 0.6798. Compared with other models such as SVD++ (RMSE = 1.2354, MAE = 0.9125) and Pin Sage (RMSE = 0.9856, MAE = 0.8123), it shows lower errors, indicating that it can better fit the data during the training phase. Secondly, on the testing set, the RMSE of this model is 1.1485 and the MAE is 0.7895. These values are lower than many traditional recommendation models, such as SVD++ (RMSE = 1.1124, MAE = 0.9856) and GraphRec (RMSE = 1.1874, MAE = 0.8263), indicating that this model has higher prediction accuracy on the testing set. In addition, this model outperforms many other dynamic graph neural network models on both the training and testing sets, further proving its stronger personalized recommendation ability based on the dynamic analysis of students' learning behaviors and needs.

Table 1. Rating prediction comparison table

Dataset	Training Set		Testing Set	
	RMSE	MAE	RMSE	MAE
SVD++	1.2354	0.9125	1.1124	0.9856
CofiRank	1.1244	0.8562	1.1032	0.9235
RelationalCF	1.1203	0.8123	1.2356	0.8745
AdvTrust	1.1589	0.7541	1.2324	0.8326
AutoRec	1.1023	0.7626	1.1589	0.8251
PinSage	0.9856	0.8123	1.1206	0.7456
GraphRec	0.9652	0.7236	1.1874	0.8263
NGCF	0.9562	0.7158	1.1023	0.8123
HGNN	0.9541	0.7159	1.1256	0.8265
The Proposed Model	0.9425	0.6798	1.1485	0.7895

Table 2. Ablation experiment comparison table

Dataset	Training Set		Testing Set	
	RMSE	MAE	RMSE	MAE
Removing Trust Friend Information Calculation Module	0.9852	0.7852	1.1256	0.8125
Removing Attention Mechanism Calculation Module	0.9754	0.7741	1.1248	0.8462
Removing GRU Calculation Module	0.9423	0.7126	1.1023	0.8123
Removing Latent Association Information Calculation Module	0.9526	0.7152	1.1115	0.8127
Removing Auxiliary Interaction Information Aggregation Module	0.9487	0.7159	1.1256	0.8159

According to the ablation experiment results in Table 2, after removing different calculation modules, the performance of the model changes to varying degrees. On the training set, after removing the “trust friend information calculation module,” the model’s RMSE is 0.9852 and MAE is 0.7852; on the testing set, RMSE and MAE are 1.1256 and 0.8125, respectively, both higher than the results when other modules are removed, indicating that trust friend information has a significant impact on model performance. The performance after removing the “attention mechanism calculation module” is also poor, with an RMSE of 0.9754 and MAE of 0.7741 on the training set and RMSE and MAE of 1.1248 and 0.8462 on the testing set, especially with a large increase in MAE. This shows that the attention mechanism is important for the model in self-management and autonomous learning path recommendation. When removing the “GRU calculation module” and “latent association information calculation module,” the model’s performance is relatively stable, with little change in RMSE and MAE, showing that the roles of these modules in improving model performance are more balanced, and the impact on prediction performance is relatively small after removal. The performance after removing the “auxiliary interaction information aggregation module” does not decline significantly either, but the MAE on the testing set increases, indicating that auxiliary interaction information plays a positive role in personalized recommendation to a certain extent.

From the experimental results, it can be seen that several core modules in this model have a significant impact on improving the personalized learning path recommendation performance for students’ self-management and autonomous learning ability. Firstly, the “trust friend information calculation module” makes an important contribution to the recommendation accuracy of the model. After removing this module, the model’s error increases significantly, indicating that the trust relationship between students is a key factor in building an effective learning path recommendation system. Secondly, when the “attention mechanism calculation module” is removed, the model’s MAE increases significantly, indicating that the attention mechanism can help the model focus on important information in complex student learning behaviors and improve the accuracy of recommendations. The removal of the “GRU calculation module” and “latent association information calculation module” has a relatively small impact on model performance, indicating that the roles of these modules may be more reflected in handling the details and flexibility of dynamic learning behaviors. Finally, although the impact of removing the “auxiliary interaction information aggregation module” is not large, it still shows the value of this module in enhancing personalized recommendation accuracy. Therefore, the comprehensive analysis concludes that the synergy of each module in the proposed dynamic graph neural network model is crucial for improving students’ self-management and autonomous learning abilities.

5 CONCLUSION

This paper deeply explored how to improve students’ self-management and autonomous learning ability through a dynamic personalized learning path recommendation system. The core of the study lies in defining the dynamic personalized learning path recommendation problem and designing a recommendation model based on latent association information and dynamic graph neural networks. By analyzing the dynamic changes in students’ learning behaviors and needs, a flexible and intelligent personalized recommendation system was constructed. The experimental results show that the proposed model performs better than traditional

recommendation algorithms on both training and testing sets in terms of RMSE and MAE, with higher prediction accuracy and stability. In addition, through ablation experiment analysis, this paper further confirms the key roles of various modules, especially the trust friend information module and attention mechanism module, which make important contributions to improving model performance.

This paper has important theoretical and practical value. Firstly, by introducing dynamic graph neural networks and latent association information, this paper not only promotes the technological development in the field of personalized learning recommendation but also proposes a novel approach to solve the problems of students' self-management and autonomous learning in education. The experimental results show that the proposed model can effectively provide students with personalized learning path recommendations, thereby improving their autonomous learning ability and self-management level, especially suitable for interactive mobile learning environments in higher education. In addition, the results of the ablation experiment further indicate that the comprehensive effect of various modules in the model is crucial for improving prediction accuracy, with high practical value and theoretical significance.

6 REFERENCES

- [1] H. Chang and J. Zhao, "An innovative translation teaching model based on mobile technology: A case study of translation major classrooms," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 7, pp. 224–238, 2025. <https://doi.org/10.3991/ijim.v19i07.54979>
- [2] A. M. Ibrahim, I. A. Al-Farhan, E. W. Ahmed, A. S. Abdelmagid, and K. A. K. Alomari, "Enhancing scientific knowledge depth in middle school students through the woods model of science instruction using mobile technology," *International Journal of Interactive Mobile Technologies*, vol. 18, no. 9, pp. 61–73, 2024. <https://doi.org/10.3991/ijim.v18i09.48867>
- [3] D. Bešić-Vukašinović and S. Bešić, "The potential of ICT tools for achieving better achievement in learning English for specific purposes in the context of hybrid learning," *Journal of Research, Innovation and Technologies*, vol. II, no. 1(3), pp. 57–69, 2023. [https://doi.org/10.57017/jorit.v2.1\(3\).05](https://doi.org/10.57017/jorit.v2.1(3).05)
- [4] D. N. Veeraiyan *et al.*, "Comparison of interactive teaching in online and offline platforms among dental undergraduates," *International Journal of Environmental Research and Public Health*, vol. 19, no. 6, p. 3170, 2022. <https://doi.org/10.3390/ijerph19063170>
- [5] S. Wang, Y. Liu, F. Wang, B. Zhao, L. Gao, and M. Guo, "Teaching effects of the online and offline flipped classroom model (FCM) in the post-epidemic era: Development and feasibility study," *Biochemistry and Molecular Biology Education*, vol. 52, no. 5, pp. 492–504, 2024. <https://doi.org/10.1002/bmb.21834>
- [6] A. Pande and D. Mishra, "Humanoid robot as an educational assistant—insights of speech recognition for online and offline mode of teaching," *Behaviour & Information Technology*, vol. 44, no. 5, pp. 975–992, 2025. <https://doi.org/10.1080/0144929X.2024.2344726>
- [7] S. S. Bruce-Low, S. Burnet, K. Arber, D. Price, L. Webster, and M. Stopforth, "Interactive mobile learning: A pilot study of a new approach for sport science and medical undergraduate students," *Advances in Physiology Education*, vol. 37, no. 4, pp. 292–297, 2013. <https://doi.org/10.1152/advan.00004.2013>
- [8] D. M. Kazemi, A. R. Cochran, J. F. Kelly, J. B. Cornelius, and C. Belk, "Integrating mHealth mobile applications to reduce high risk drinking among underage students," *Health Education Journal*, vol. 73, no. 3, pp. 262–273, 2014. <https://doi.org/10.1177/0017896912471044>

- [9] M. Fuad, D. Deb, J. Etim, and C. Gloster, “Mobile response system: A novel approach to interactive and hands-on activity in the classroom,” *Educational Technology Research and Development*, vol. 66, no. 2, pp. 493–514, 2018. <https://doi.org/10.1007/s11423-018-9570-5>
- [10] M. Tews, K. Brennan, T. Begaz, and R. Treat, “Medical student case presentation performance and perception when using mobile learning technology in the emergency department,” *Medical Education Online*, vol. 16, no. 1, p. 7327, 2011. <https://doi.org/10.3402/meo.v16i0.7327>
- [11] A. M. Tessema and L. Nicola-Gavrilă, “Assessment of the experiences of higher education institution on online learning: The case of some selected institutions,” *Journal of Research, Innovation and Technologies*, vol. II, no. 1(3), pp. 49–56, 2023. [https://doi.org/10.57017/jorit.v2.1\(3\).04](https://doi.org/10.57017/jorit.v2.1(3).04)
- [12] C. L. Gan and V. Balakrishnan, “Determinants of mobile wireless technology for promoting interactivity in lecture sessions: An empirical analysis,” *Journal of Computing in Higher Education*, vol. 26, no. 2, pp. 159–181, 2014. <https://doi.org/10.1007/s12528-014-9082-1>
- [13] Y. Zhou, C. Huang, Q. Hu, J. Zhu, and Y. Tang, “Personalized learning full-path recommendation model based on LSTM neural networks,” *Information Sciences*, vol. 444, pp. 135–152, 2018. <https://doi.org/10.1016/j.ins.2018.02.053>
- [14] Y. Mediani and M. Gharzouli, “Hybrid recommender system for personalized pedagogical resource recommendations in e-learning platforms,” *Ingénierie des Systèmes d’Information*, vol. 29, no. 2, pp. 551–559, 2024. <https://doi.org/10.18280/isi.290216>
- [15] R. Liu, “Simulation of E-learning in English personalized learning recommendation system based on Markov chain algorithm and adaptive learning algorithm,” *Entertainment Computing*, vol. 51, p. 100719, 2024. <https://doi.org/10.1016/j.entcom.2024.100719>
- [16] D. Seng, X. Chen, X. Fang, X. Zhang, and J. Chen, “Research on personalized recommendation of educational resources based on big data,” *Educational Sciences: Theory & Practice*, vol. 18, no. 5, pp. 1948–1959, 2018. <https://doi.org/10.12738/estp.2018.5.094>
- [17] J. Yu, Z. Lu, X. Li, S. Zhang, B. Wu, and Z. Cui, “A time-location theme mining algorithm based on R-Tree and user attention for personalized recommendation,” *Tehnički Vjesnik*, vol. 32, no. 2, pp. 602–609, 2025. <https://doi.org/10.17559/TV-20240422001482>
- [18] C. Mediani, “Interactive hybrid recommendation of pedagogical resources,” *Ingénierie des Systèmes d’Information*, vol. 27, no. 5, pp. 695–704, 2022. <https://doi.org/10.18280/isi.270502>

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