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PAPER

The Application of a Mobile Learning-Based Interactive Education Platform for the Creation of Animation in University Settings

Qi Huang (✉)

Department of Digital Art and Design, Hebei Art & Design Academy, Baoding, China

13331281863@163.com

ABSTRACT

Animation creation, as an interdisciplinary subject that blends art and technology, places high demands on students' creativity, comprehensive skills, and practical capabilities. Traditional teaching models often fall short in meeting students' needs for personalized learning and real-time interaction, highlighting the urgent need for innovation through mobile learning platforms. Although some existing studies have attempted to introduce personalized recommendation mechanisms into educational platforms, their application in animation education remains limited, characterized by simplistic models and insufficient exploration of interactive behaviors. In particular, leveraging learners' implicit mobile interaction relationships for resource recommendation is still in its early stages. This study focuses on the design and implementation of a mobile learning-based interactive education platform tailored for university-level animation creation, aiming to enhance the precision of resource recommendations and the personalization of learning experiences. The research addresses two main aspects: first, it systematically explores the issue of personalized animation learning resource recommendation based on implicit interaction relationships, highlighting their potential value in recommendation mechanisms; second, it proposes a recommendation model integrating coupled graph modeling, attribute representation learning, interaction representation learning, and a prediction layer, offering a technical framework for intelligent recommendation in animation education. The findings are expected to promote deeper integration of mobile learning platforms in university animation education and enhance the effectiveness of personalized teaching.

KEYWORDS

mobile learning, animation creation, personalized recommendation, implicit interaction relationships, educational platform, higher education

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1 INTRODUCTION

With the rapid development of information technology and the popularization of mobile internet and smart terminal devices [1–4], mobile learning, as a new form of learning, has gradually attracted widespread attention in the field of education. Especially in higher education, how to use mobile devices to assist learning [5, 6] and improve learning effectiveness has become a research hotspot. Animation creation, as a unique art form, covers multiple aspects such as painting, design, and story conception [7–10] and requires students not only to have solid basic knowledge in the learning process but also to possess strong innovation and practical abilities [11, 12]. Therefore, how to combine mobile learning technology to provide a more personalized and interactive learning platform for animation creation education in higher education institutions has become an urgent problem to be solved.

However, although many studies have explored the construction and application of personalized education platforms based on mobile learning, most of the research mainly focuses on the proposal of theoretical frameworks and the realization of technologies [13–16], lacking in-depth exploration of the specific subject of animation creation. For example, the personalized learning recommendation systems constructed in literature [17] mostly focus on the recommendation of subject knowledge while lacking accurate recommendation of animation creation learning resources. Especially in dynamic learning environments, how to accurately analyze student needs and recommend appropriate learning resources through implicit mobile interaction relationships remains a technical problem to be solved. At the same time, the study in literature [18] also has certain limitations in model construction, such as ignoring the multidimensional interactions in the learning process and the influence of complex contexts. These problems limit the application effect of personalized recommendation systems in animation creation education.

This paper mainly studies the personalized recommendation problem of animation creation learning resources based on implicit mobile interaction relationships. Specifically, the research content of this paper includes two parts: the first is the description of the personalized recommendation problem of animation creation learning resources based on implicit mobile interaction relationships, analyzing in depth the implicit characteristics of interaction relationships in current education platforms and their impact on learning resource recommendation; the second is the construction of a personalized recommendation model for animation creation learning resources based on implicit mobile interaction relationships. A coupled graph construction method based on animation creation mobile interaction scenarios is proposed, and through modules such as attribute representation learning, interaction representation learning, and prediction layer, learning resources that meet student needs are accurately recommended. This study not only helps promote the personalized development of animation creation education but also provides theoretical basis and practical reference for the optimization and innovation of mobile learning platforms.

2 DESCRIPTION OF PERSONALIZED ANIMATION CREATION LEARNING RESOURCE RECOMMENDATION PROBLEM

At present, university animation creation teaching faces the diversification of teaching content and student needs, while traditional teaching models are difficult to effectively cope with this complexity. At the same time, traditional animation creation teaching often relies on fixed course content and teaching methods, lacking flexible interactivity and personalized learning paths, which leads to limitations in students' learning motivation and effectiveness. This paper chooses to conduct personalized recommendation research based on implicit mobile interaction relationships, which can break through this limitation and promote more autonomy and creativity in the learning process. By constructing a recommendation system based on student interaction behavior, the platform can adjust recommended content in real time according to students' learning progress and interest changes, thereby improving the relevance and effectiveness of learning.

The research objective of this paper is to recommend personalized animation creation learning resources that meet the needs and preferences of target student *i* under animation creation mobile interaction scenario *z*. For a given set of students *I*, learning resources *X*, and animation creation mobile interaction scenarios *Z*, the task of this study is to customize a personalized animation creation learning resource recommendation list *Ei* for student *i* in mobile interaction scenario *z*, where $Ei = \{x_1, x_2, \ldots, x_v \mid iz, x_u \in X, z \in Z, i \in I\}$. *v* is the length of the recommendation list, and $|iz$ represents student *i* in animation creation mobile interaction scenario *z*. Specifically, the recommendation problem in this study can be described by constructing a "student-animation creation scenario-learning resource" coupled graph model, where each node represents a student, a learning resource, or an animation creation scenario, and the relationship between students and learning resources is represented by their interaction behavior under specific scenarios. Through this graph structure, the needs and preferences of students under different scenarios can be further mined from the perspectives of attribute learning and interaction learning. In attribute learning, we focus on how individual characteristics of students and content attributes of learning resources affect students' choices, while in interaction learning, we focus more on how interaction patterns, frequencies, and intensities between students and learning resources affect the recommendation effect. Finally, by predicting the selection probability of a student for a certain learning resource under the current scenario, the model can provide a personalized learning resource recommendation list based on regression methods.

3 CONSTRUCTION OF RECOMMENDATION MODEL BASED ON IMPLICIT MOBILE INTERACTION RELATIONSHIP

The personalized animation creation learning resource recommendation model includes four parts: construction of the coupling graph based on animation creation mobile interaction scenarios, attribute representation learning, interaction representation learning, and prediction layer.

3.1 Construction of scenario-based coupling graph

The construction of the coupling graph $H_{UC} = (N_{UCA}, R_{UCA})$ is the key starting point of the entire recommendation model. Its purpose is to systematically and structurally represent the complex relationships among students, animation creation mobile interaction scenarios, and learning resources. Specifically, in the construction process of the node set N_{UCA}, the study takes student *i*, animation creation mobile interaction scenario *z*, and learning resource *x* as the three core types of nodes. Among them, student nodes not only represent entities but also include important attribute information describing their individual differences. In order to enable the model to effectively identify these individual characteristics, the study encodes the gender, age, and device type used by the student using one-hot encoding, then concatenates the vectors and uses embedding technology to map these discrete features into low-dimensional continuous dense vectors, thus generating the node representation of the student. Similarly, for learning resource nodes, the system extracts the attributes of the learning resource and relevant information of the developer and uses the same encoding and embedding method to generate the node vector of the learning resource. Through the above processing, all nodes not only have structural positional representations but also semantic vector representations that can be used for subsequent feature learning.

In the construction process of the edge set R_{UCA}, the study defines the connection relationships between nodes by analyzing students' usage behavior of learning resources in specific animation creation mobile interaction scenarios. Specifically, when a student i_u uses learning resource x_l in a specific scenario z_k, the model establishes an edge between nodes i_u and z_k, and an edge between z_k and x_l, and adds 1 to the weight of the corresponding edge, indicating that there is one interaction behavior. If no such behavior occurs, the edge is not established or the weight is 0, which is reflected in the graph as no connection relationship. The weight of the edge not only indicates whether there is a connection between the nodes, but also quantifies the strength of the connection, that is, the frequency of interaction.

3.2 Attribute representation learning

In order to better explore the attribute factors of the coupling graph H_{UC}, this paper uses implicit relationships to decompose the coupling graph into three homogeneous graphs: student graph H_i, animation creation mobile interaction scenario graph H_z, and learning resource graph H_x. Figure 1 shows the schematic diagram of the construction process of homogeneous graphs. The specific decomposition steps include the following four aspects:

1. First, decompose the coupling graph H_{UCA} into H_{iz}, that is, a graph with students and animation creation mobile interaction scenarios as nodes. In this process, the learning resource nodes in the original coupling graph are deleted, while the edges between students and animation creation mobile interaction scenarios are retained. The core purpose of this operation is to explore the regular behavioral patterns of students in different animation creation mobile interaction scenarios through the H_{iz} graph. For example, students' daily activities often have certain regularity—they usually participate in specific animation creation activities during fixed time periods, and these activity scenarios also have their fixed appearance patterns in students' daily lives. By analyzing the H_{iz} graph, it is possible to identify potential relational patterns between students and animation creation mobile interaction scenarios, providing valuable behavioral features for the subsequent recommendation model. Next, decompose the coupling graph H_{UCA} into H_{zx} and H_{ix}. For H_{zx}, student nodes are deleted, retaining animation creation mobile interaction scenario nodes and learning resource nodes and the edges between them. Through the H_{zx} graph, the study can explore the adaptive relationship between specific animation creation mobile interaction scenarios and learning resources. Application programs are often designed to meet the needs under specific scenarios, and specific animation creation scenarios also

require certain types of applications for support. By analyzing the H_{zx} graph, it is possible to understand which applications are more applicable under specific scenarios, thereby helping to optimize resource recommendation. Finally, for H_{ix}, animation creation mobile interaction scenario nodes are deleted, retaining student and learning resource nodes and the edges between them. The H_{ix} graph can reflect students' selective preferences for learning resources. Students usually choose learning resources that match their interests and needs, and each learning resource also attracts specific types of students.

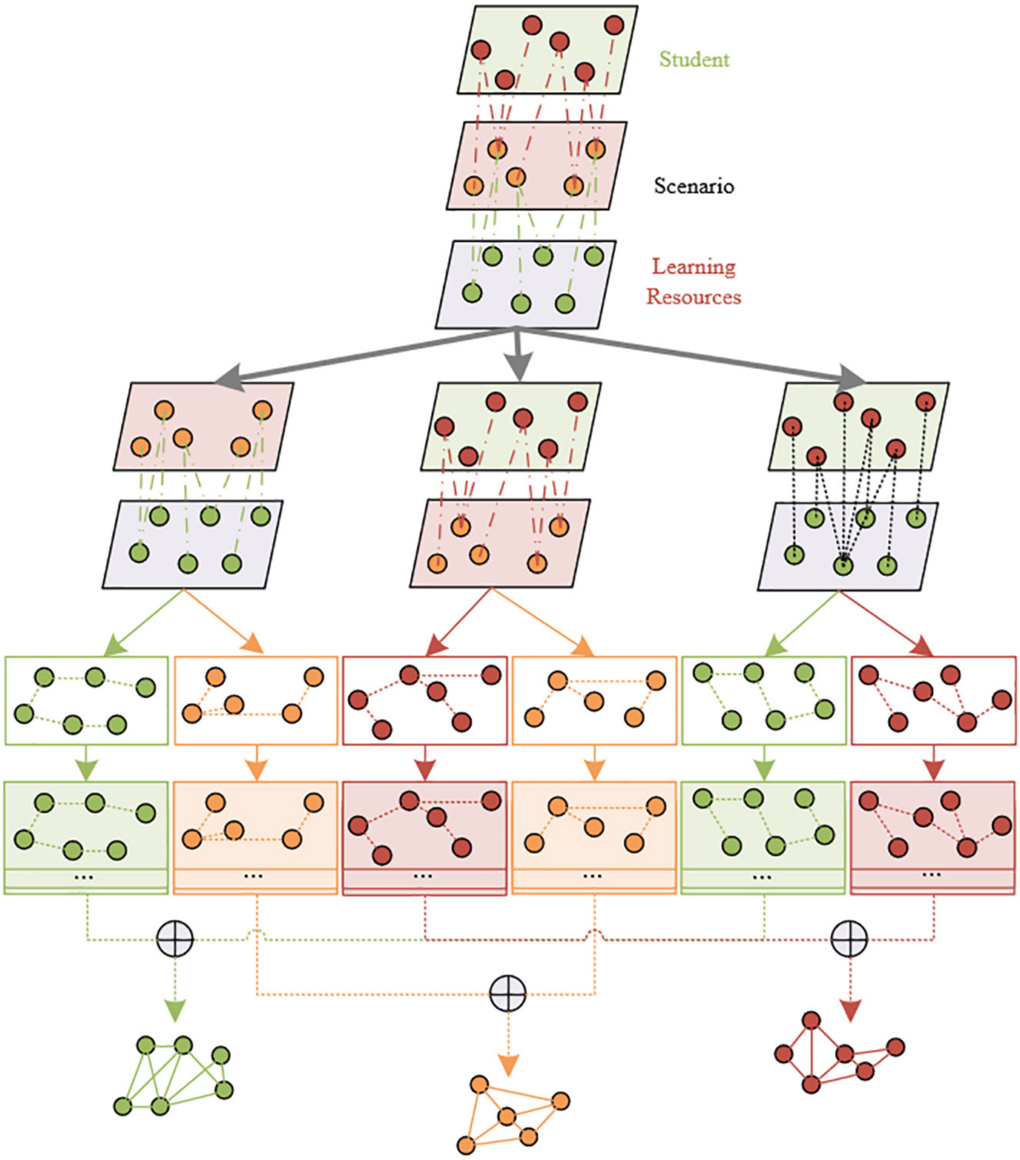


Fig. 1. Schematic diagram of the homogeneous graph construction process

2. First, the decomposed graphs H_{iz}, H_{zx}, and H_{ix} are further divided into six homogeneous weighted graphs to deeply explore the relationships between nodes from different perspectives. Taking H_{iz} as an example, it is split into two homogeneous graphs H_i and H_z. H_i is a homogeneous graph with students as nodes. If two students i_u and i_k appear together in the same animation creation mobile interactive context, then an edge is formed between them, and the weight of the edge q_{uk}

reflects the strength of the relationship between i_u and i_k. This edge weight can be calculated based on the interaction frequency of students in the same context; students who interact frequently will have higher edge weights, and vice versa. On the other hand, H_z is a homogeneous graph with animation creation mobile interactive contexts as nodes. If two animation creation mobile interactive contexts involve similar student groups or are used by similar learning resources, then an edge is formed between them, and the edge weight indicates the similarity between the two contexts. Assume that the maximum value of the edge weight in the H_{iz} graph is denoted by B_{MAX}. The nodes connected to both i_u and i_k are denoted as F_{uk}, and the number of such nodes is denoted as $|F_{uk}|$. The number of times student i_u appears in context z_x is denoted as b_{ux}. The explicit relationship value between nodes i_u and i_k is represented by q_{uk}. The calculation formula is as follows:

$$q_{uk} = \frac{B_{MAX} - \frac{1}{|F_{uk}|}\sum_{z_y \in F_{ukj}} |b_{uy} - b_{ky}|}{B_{MAX}} \tag{1}$$

3. In each iteration, the weight of a node will be updated based on the attributes and relationships of neighboring nodes. This process captures implicit relationships between nodes, meaning it not only relies on explicit interaction data but also explores deeper latent connections. For example, in *Gu*, the relationship between student nodes depends not only on direct interaction frequency but may also be influenced by indirect relationships between other students; similarly, in *Gc*, the relationships between animation creation mobile interactive contexts are updated through indirect associations between contexts. Through this iterative process, the model can discover more accurate and detailed relationships between nodes, further enhancing the personalization and precision of recommendations. Assume the number of iterations is denoted by m, the loss coefficient by ϕ, and the penalty factor by ζ. The model hyper-parameters are denoted by ϕ and ζ. The iterative computation process for each homogeneous graph is as follows:

$$q_{uk}^{m} = (1-\varphi)q_{uk}^{m-1} \tag{2}$$

$$\varphi = \text{sigmoid}\left(\frac{1}{|F_{uk}|}\zeta\right) \tag{3}$$

$$q_{uk}^{0} = q_{uk} \tag{4}$$

Assume that the product of two vectors is denoted by ⊗, and the feature similarity between i_u and i_k is represented by $i_u \otimes i_k$. The neighbors of i_u are denoted by V_u. The model hyper-parameters are denoted by σ_0 and σ_1, where $\sigma_0 + \sigma_1 = 1$. The final implicit relationship value between i_u and i_k is represented by e_{uk}^{m}, and its calculation process is as follows:

$$e_{uk}^{m} = \sigma_0 q_{uk}^{m} + \sigma_1 \frac{i_u \otimes i_k}{\sum_{i_a \in V_u}(i_u \otimes i_a)} \tag{5}$$

4. The model merges the six homogeneous graphs into three final homogeneous graphs H_i^*, H_z^*, and H_a^* based on node types. This step integrates the previously

decomposed and updated graphs to better reflect the overall relationships among students, contexts, and learning resources.

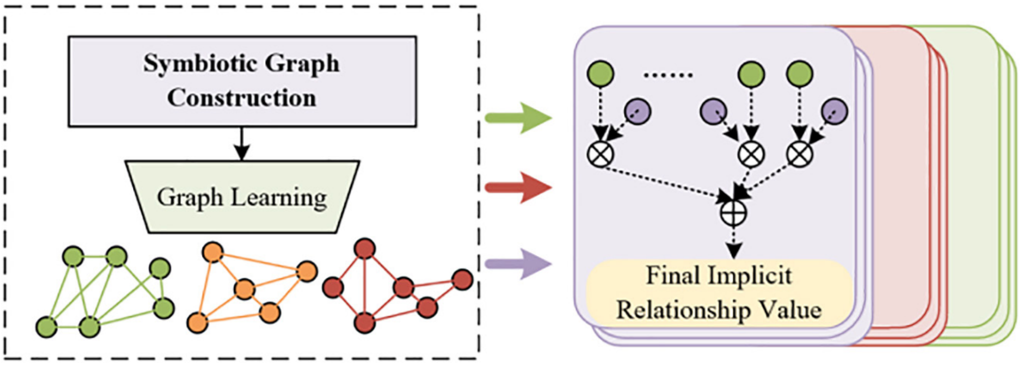


Fig. 2. Schematic diagram of the model attribute representation learning principle

Figure 2 illustrates the schematic diagram of the model attribute representation learning principle. The node representation learning process is achieved through the aggregation operation on the graphs H_i^*, H_z^*, and H_a^*, thereby obtaining the final representation of each node. Taking H_i^* as an example, the representation of student nodes depends not only on their own attributes but also on their neighboring nodes—i.e., other students who participate in the same animation creation mobile interactive context. By aggregating the relationship strength with these student nodes, the model can capture the interaction patterns between students, thereby providing more refined input information for personalized recommendations. Assume the target node is represented by i_u, and the top v neighboring nodes of i_u calculated based on e_{uk}^m are denoted by V_u^v. The globally shared aggregation functions are represented by d_{AG}^{gu} and d_{AG}^{mp}. d_{AG}^{mp} is used to aggregate student neighbor information, while d_{AG}^{gu} aggregates the target student and neighbors. The aggregation process is as follows:

$$i_u = d_{AG}^{gu}(i_u, d_{AG}^{mp}(V_u^v)) \tag{6}$$

For $d_{AG}^{mp}(V_u^v)$, the personalized animation creation learning resource recommendation model introduces an attention mechanism for precise computation. Assume that the hyperparameters are represented by q_i^{mp} and y_i^{mp}, the concatenation operation of two vectors is denoted by ||, and the nonlinear activation function is represented by tanh. The aggregation formula for $d_{AG}^{mp}(V_u^v)$ is as follows:

$$d_{AG}^{mp}(Vu_i^v) = \sum_{i_k \in V_u^v} i_k \times \frac{\exp(X_{uk})}{\sum_{i_l \in V_u^v} \exp(X_{ul})} \tag{7}$$

X_{uk} describes the importance of neighbor i_k to student i_u, and the expression is as follows:

$$X_{uk} = (i_u \otimes i_k)^T \tanh(q_i^{mp} \cdot \left[i_u \,||\, i_k\right] + y_i^{mp}) \tag{8}$$

Assume the hyperparameters are represented by i_i^{gu} and y_i^{gu}, and the nonlinear activation function is represented by θ. The high-level aggregation formula d_{AG}^{gu} is as follows:

$$d_{AG}^{gu}(i_u, d_{AG}^{mp}(V_u^v)) = \theta(i_i^{gu} \cdot [i_u + d_{AG}^{mp}(V_u^v)] + y_i^{gu}) \tag{9}$$

To obtain deeper representations, the personalized animation creation learning resource recommendation model stacks multiple aggregation layers to gather information from more neighbors. The stacking process is as follows:

$$i_u^f = d_{AG}^{gu}(i_u^{f-1},(d_{AG}^{mp}(V_u^v))^{f-1}) \tag{10}$$

For graphs H_z^* and H_x^*, similar steps are used to compute z_u^f and x_u^f.

3.3 Interaction representation learning

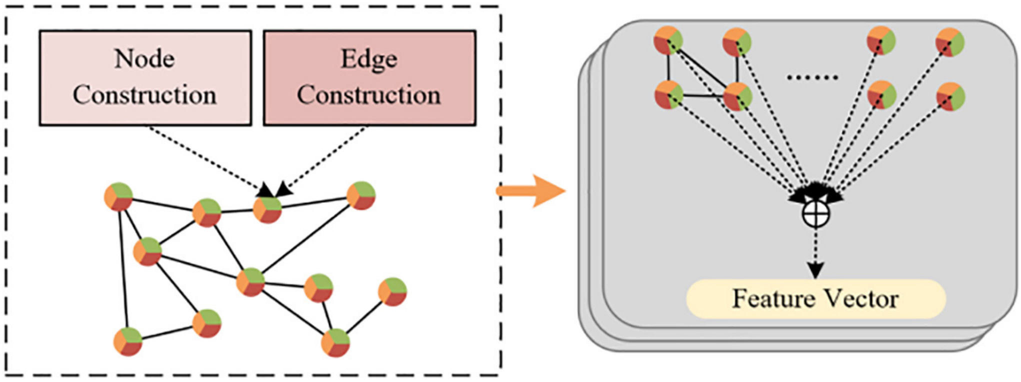


Fig. 3. Schematic diagram of the interaction representation learning principle of the model

The construction of the interaction graph H_{IN} aims to delve into the external motivational factors within the H_{UCA} graph, specifically the interactive relationships among students, animation creation, mobile interactive scenarios, and learning resources. Firstly, the node set N_{IN} in the interaction graph H_{IN} comprises three types of nodes: students, animation creation mobile interactive scenarios, and learning resources. The construction of these nodes is intended to reflect the dynamic interactions between students and scenarios, as well as between students and learning resources. Assuming that the number of times student i_o uses learning resource x_l in scenario z_w is represented by U_{owl}, and the vectors of i_o, z_w, and x_l are denoted as n_o^i, n_w^z, and n_l^x respectively, with their total number of interactions represented by V_o^i, V_w^z, and V_l^x. FINTa denotes the degree of node N_{INT}^a, i.e., the number of neighbors of n_{INT}^a. The constructed node information n_{IN}^a is represented by the following formula:

$$n_{IN}^a = \left\langle U_{owl}, n_o^i, n_w^z, n_l^x, V_o^i, V_w^z, V_l^x, F_a^{INT} \right\rangle \tag{11}$$

The edge set R_{IN} in the interaction graph H_{IN} further enhances the model's understanding of external motivations by capturing the relationships among different types of nodes. In H_{IN}, the existence of an edge not only reflects the interactive relationships among students, animation creation mobile interactive scenarios, and learning resources but also includes the strength of these interactions. The weight of an edge can be defined based on various factors such as the frequency, duration, and intensity of interactions between students and scenarios or learning resources. Assuming the similarity calculation function is denoted by *SIM* (.), and the nonlinear activation function by θ, the following formula provides the calculation of the weight between each pair of nodes in H_{IN}:

$$w_n^{ac} = \theta(SIM(n_{IN}^a, n_{IN}^c)) \tag{12}$$

To further simplify the interaction graph, assuming the model hyperparameter is denoted by λ, and $r_n^{ac} = 0$ indicates the edge r_n^{ac} is not retained, otherwise it is retained. The removal of weakly related edges is performed according to the following formula:

$$r_n^{ac} = \begin{cases} 0, \text{ if } w_n^{ac} \le \lambda \\ 1, \text{ others} \end{cases} \tag{13}$$

Figure 3 presents the schematic diagram of the interaction representation learning principle of the model. The node aggregation in interaction representation learning is achieved through the construction of multi-layer weighted graphs and interaction representation learning. Firstly, the model identifies neighbor relationships by calculating the similarity between nodes. Specifically, for any two nodes a and c in the H_{IN} graph, the model uses the following formula to calculate their similarity, which is based not only on their direct interactions but also on their structural similarity within the graph. The similarity between nodes reflects the strength of their connections in the graph, providing a foundation for subsequent aggregation processes. Assuming the j-th order neighbor degree sequences of n_{IN}^a and n_{IN}^c are denoted by $t(E_j(n_{IN}^a))$ and $t(E_j(n_{IN}^c))$ respectively, and the distance between two ordered sequences F_1 and F_2 is represented by $h(F_1, F_2)$, the structural similarity degree of the j-th order neighbors of n_{IN}^a and n_{IN}^c is denoted by $d^j(a,c)$, calculated as follows:

$$\begin{aligned} & d^j(a,c) = d^{j-1}(a,c) + h(t(E_j(n_{IN}^a)), t(E_j(n_{IN}^c))) \\ & j \ge 0 \;\; AND \;\; \left|E_j\left(n_{IN}^c\right)\right|, \left|E_j\left(n_{IN}^c\right)\right| > 0 \end{aligned} \tag{14}$$

The similarity between two interaction nodes is denoted by d^1 (a,c), calculated as follows:

$$d^{-1}(a,c) = -\text{sim}(n_{IN}^a, n_{IN}^c) \tag{15}$$

Here, j_{MAX} represents the maximum value of j, which is a model hyper-parameter. To ensure some level of similarity between n_{IN}^a and n_{IN}^c, the model only calculates the similarity $d^j(a,c)$ within three hops. Subsequently, the model constructs a multi-layer weighted graph, where the edge weight $\mu_j(a,c)$ of each layer is calculated using the following formula, considering the interaction strength and similarity between nodes:

$$\mu_j(a,c) = e^{-d^j(a,c)}, j = 0,1,\ldots \tag{16}$$

Layers are connected through directed edges. That is, for any node n_{IN}^a in the j-th layer, there exist two directed edges (a_j, a_{j-1}) and (a_j, a_{j+1}). Assuming the number of edges pointing to n_{IN}^a in the j-th layer with weights greater than the average weight of that layer is denoted by $\Pi^j(a)$, their weights are:

$$\mu(a_j, a_{j-1}) = \log(\Pi^j(a) + r), j = 0,1,\ldots, j-1 \tag{17}$$

$$\mu(a_j, a_{j-1}) = 1, j = 1,\ldots, j \tag{18}$$

$$\Pi^j(a) = \sum_{n_{INT}^c \in N_{INT}} 1(\mu_j(a,c) > \bar{\mu}_j) \tag{19}$$

In each layer of the graph, nodes are not fully connected. Therefore, the model samples neighbor nodes through random walks, with a sampling probability of w_j, enabling effective information propagation and learning based on the characteristics and structure of nodes in each layer. Assuming the probability of walking from node a in the j-th layer to node n_{IN}^{c} in the same layer is denoted by $w_j(a, c)$, and the probability of walking to the (j+1)-th layer is denoted by $o_j(a_j, a_{j+1})$, the calculation formulas are:

$$w_j(a,c) = \frac{e^{-d^j(a,c)}}{\sum_{n_{INT}^c \in N_{INT}, c \neq a} e^{-d^j(a,c)}} \tag{20}$$

The sampling probability o_j of the adjacent layer is calculated as:

$$o_j(a_j, a_{j+1}) = \frac{\mu(a_j, a_{j+1})}{\mu(a_j, a_{j+1}) + \mu(a_j, a_{j+1})} \tag{21}$$

Next, the model updates the feature vector of each node by aggregating the information of sampled nodes. For each student node, the model concatenates the feature vectors of the student and all its neighbor nodes, then uses embedding methods to map the concatenated feature vector to a fixed-length vector, which serves as the final feature representation of the student node. Similarly, animation creation mobile interactive scenarios and learning resource nodes undergo the same process, aggregating information from their neighbor nodes to generate the final feature vectors for each scenario, and learning resource. These feature vectors reflect the potential attributes and relationships of each node in the interaction graph, providing rich input information for personalized animation creation learning resource recommendations. Assuming the neighbor nodes of n_{IN}^{c} are denoted by V^a, and the number of nodes in V^a is represented by $|V^a|$, the calculation formula is:

$$n_{IN}^{a} = n_{IN}^{a} + \frac{1}{|V^a|} \sum_{c \in V^a} \mu_j(a,c) \cdot n_{IN}^{c} \tag{22}$$

3.4 Prediction layer

The core task of the prediction layer is to perform personalized learning resource prediction based on the feature vectors of students, animation creation mobile interactive scenarios, and learning resources. First, for each student, animation creation mobile interactive scenario, and learning resource, the model connects their attribute information with interaction representations to obtain a comprehensive feature representation. Similarly, animation creation scenarios and learning resource nodes also generate corresponding comprehensive features based on their attributes and interaction representations. These feature vectors are denoted as i_u^M, z_u^M, and x_u^M, representing the embedding representations of students, scenarios, and learning resources, respectively. Next, the model adopts a multi-layer perceptron (MLP) as the implementation of the prediction function o. In this study, i_u^M, z_u^M, and x_u^M are used as input features of the MLP, and through the computation of two hidden layers, a final prediction value is output, which represents the relevance or suitability of the recommended learning resource:

$$\hat{b}_u = o(i_u^M, z_u^M, x_u^M) \tag{23}$$

3.5 Model optimization

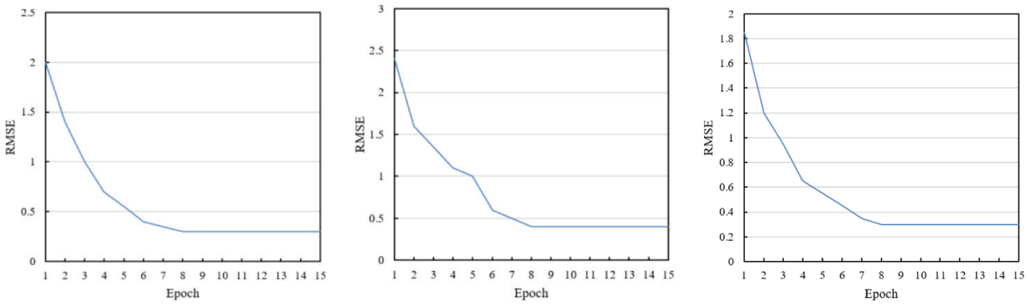
The personalized animation creation learning resource recommendation model makes recommendations based on the preference probability of target student i for learning resource x under animation creation mobile interactive scenario z, which is a typical regression problem. Therefore, the personalized animation creation learning resource recommendation model trains the model through a loss function *loss*. Suppose the recommendation list is denoted as P, and the length of the list is denoted as $|P|$. Model hyper-parameters are denoted as Φ_U, then:

$$loss = \frac{1}{|P|} \sum_{(x,u)\in P} (b_{xu} - \hat{b}_{xu})^2 + \eta_U \left\| \Phi_U \right\|^2 \tag{24}$$

The loss function *loss* consists of two parts: $1/|P| \sum_{(x,u)\in P} (b_{xu} - \hat{b}_{xu})^2$ is used to measure the loss in the recommendation framework, and $\eta_U \left\| \Phi_U \right\|^2$ is the $L2$ regularization term, used to control model complexity and avoid overfitting.

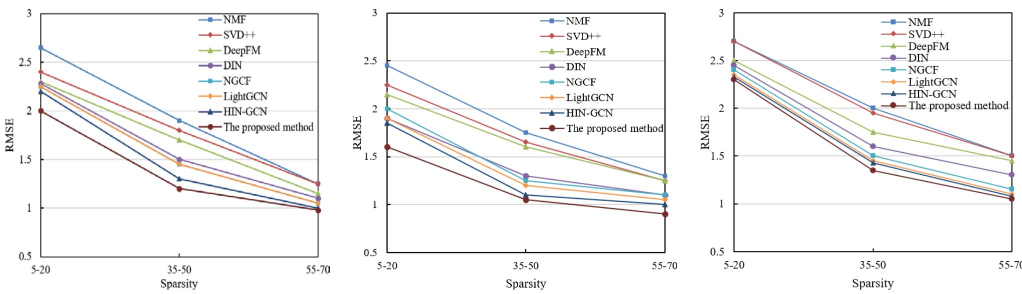
4 EXPERIMENTAL RESULTS AND ANALYSIS

According to the experimental results of the three datasets Moodle, EdNet, and ASSISTments in Figure 4, we can observe the gradually decreasing trend of root mean square error (RMSE) values during the training process of 15 epochs on different datasets. On the Moodle dataset, the RMSE is two at epoch one, and then gradually decreases, finally stabilizing at 0.3 at epoch 15. The EdNet dataset shows a similar trend, decreasing from 2.4 at epoch 1 to 0.4 at epoch 15, indicating that the model can effectively optimize and gradually converge. The performance on the ASSISTments dataset is also quite significant, with RMSE decreasing from 1.85 at epoch 1 to 0.3 at epoch 15. These data show that as the training progresses, the model's performance on all three datasets improves significantly, with the error continuously reducing, showing good convergence.



a) ***Moodle*** **dataset** **b)** ***EdNet*** **dataset** **c)** ***ASSISTments*** **dataset**

Fig. 4. Convergence experiments of the proposed model on three datasets



a) ***Moodle*** **dataset** **b)** ***EdNet*** **dataset** **c)** ***ASSISTments*** **dataset**

Fig. 5. Recommendation performance of the proposed model under different sparsity scenarios

As shown in Figure 5, the proposed model demonstrates significant advantages in recommendation performance under different sparsity conditions on the three datasets. On the Moodle dataset, the RMSE values of the proposed method are 2 when sparsity is between 5 and 20, 1.2 when between 35 and 50, and 0.98 when between 55 and 70, all showing strong accuracy, especially under high sparsity (55–70). On the EdNet dataset, the proposed method also exhibits a similar trend, with RMSE values of 1.6, 1.05, and 0.93 respectively, indicating that as sparsity increases, the model can continue to optimize recommendation accuracy. On the ASSISTments dataset, the RMSE values under different sparsity levels are 2.3, 1.35, and 1.05, respectively, showing the model's stability and efficiency in handling sparse data. Compared with other traditional methods (such as NMF, SVD++, DeepFM, etc.), the performance of the proposed method consistently remains superior, especially under high sparsity, where the recommendation effect of the model is more prominent.

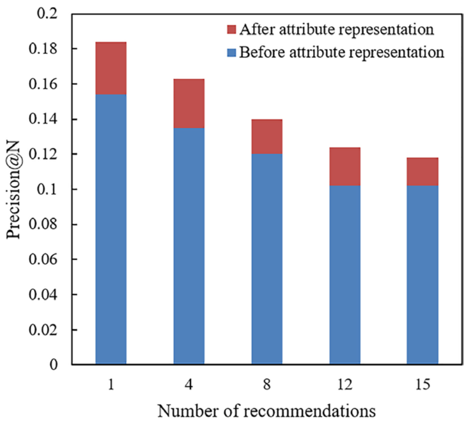


Fig. 6. Impact of attribute representation in the proposed model

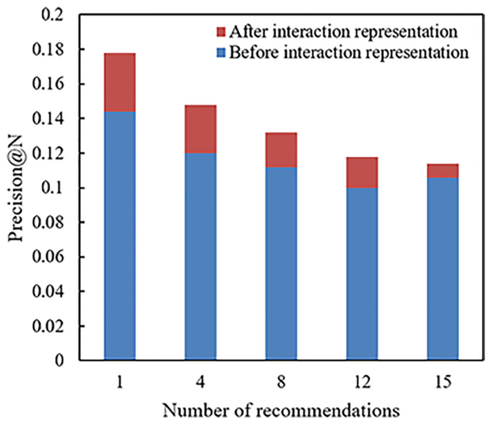
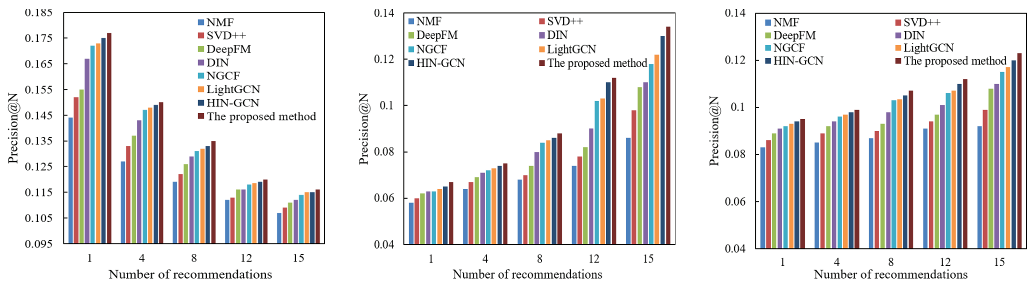


Fig. 7. Impact of interaction representation in the proposed model

According to the recommendation accuracy data before and after attribute representation shown in Figure 6, it can be observed that attribute representation significantly improves the recommendation effect of the model. When the number of recommendations is 1, the accuracy before attribute representation is 0.154, and after attribute representation, it increases to 0.157; when the number of recommendations is 4, it increases from 0.135 to 0.163, showing a noticeable improvement. As the number of recommendations increases, the impact of attribute representation becomes more significant. When the number of recommendations is 12, the accuracy increases from 0.102 to 0.124, demonstrating a continuous optimization trend. Finally, when the number of recommendations is 15, the accuracy before and after attribute representation is 0.102 and 0.118 respectively, further verifying the positive impact of attribute representation.

According to the recommendation accuracy data before and after interaction representation shown in Figure 7, it is clear that the introduction of interaction representation significantly improves the recommendation performance of the model. When the number of recommendations is 1, the accuracy before interaction representation is 0.144, and after interaction representation, it increases to 0.178, showing a significant improvement. As the number of recommendations increases, the impact of interaction representation becomes more obvious. When the number of recommendations is 4, the accuracy increases from 0.12 to 0.148, with an improvement of nearly 30%. When the number of recommendations is 8, 12, and 15, the accuracy after interaction representation compared to before is 0.1322 vs. 0.112, 0.118 vs. 0.1, and 0.114 vs. 0.106 respectively, all showing a continuous optimization trend, indicating that interaction representation plays a stable and continuous role in improving recommendation accuracy.

According to the recommendation accuracy data in Figure 8, the proposed method shows good recommendation performance on all three datasets under different recommendation quantity conditions. On the Moodle dataset, as the number of recommendations increases, the accuracy of the proposed method gradually decreases but remains at a high level. For example, when the number of recommendations is 1, its accuracy is 0.177, and when the number of recommendations is 15, the accuracy is 0.116, which is better than other models. On the EdNet dataset, the proposed method also performs prominently, with an accuracy of 0.067 when the number of recommendations is 1, and 0.134 when the number is 15, both higher than those of other comparison models. On the ASSISTments dataset, the proposed method also significantly outperforms other methods, with an accuracy of 0.095 when the number of recommendations is 1 and 0.123 when the number is 15. This indicates that the proposed method still maintains high recommendation performance under different sparsity conditions.



a) ***Moodle*** **dataset** **b)** ***EdNet*** **dataset** **c)** ***ASSISTments*** **dataset**

Fig. 8. Comparison of recommendation accuracy of different models

5 CONCLUSION

This paper investigated the personalized anime creation learning resource recommendation problem based on implicit mobile interaction relationships and proposes a coupled graph construction method based on anime creation mobile interaction scenarios. With the help of modules such as attribute representation learning, interaction representation learning, and prediction layer, the model accurately recommends learning resources that meet students' needs. The study shows that by introducing implicit interaction relationships, the accuracy of the learning resource recommendation system can be significantly improved, and more personalized learning resource recommendations can be provided for students, especially in the field of anime creation, which has a high degree of personalized demand. This study not only promotes the personalized development of anime creation education but also provides a theoretical basis and practical reference for the optimization and innovation of mobile learning platforms, with high academic and practical application value.

However, although this paper has achieved significant results in improving recommendation accuracy, there are still some limitations. First, although the proposed model shows good performance on some datasets, its generalization ability may be limited by the size and diversity of the datasets, especially in more complex educational scenarios where more optimization may be required. Secondly, this study mainly focuses on the field of anime creation, and future research can extend this model to other educational fields to further verify its effectiveness. In addition, with the development of mobile learning technology, how to better integrate real-time learning data, cross-platform learning activities, and dynamic feedback will be an important direction for future research. These studies can further improve personalized learning resource recommendation systems and promote the intelligent and personalized development of educational platforms.

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7 AUTHOR

Qi Huang studied at the Beijing Film Academy from 2006 to 2010 and obtained a bachelor's degree in 2010. Since 2011, she has been working at the Hebei Art & Design Academy. From 2021 to 2023, she studied at Vitebsk State University in Belarus and obtained a master's degree. She is mainly engaged in teaching 3D model production for anime and gaming majors (E-mail: 13331281863@163.com).