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PAPER

Optimization of Personalized English Learning Paths through Mobile Interaction Technology

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ABSTRACT

With the development of information technology (IT), particularly the widespread application of mobile internet and smart devices, traditional methods of English language learning can no longer meet the personalized needs of modern learners. The design and recommendation of personalized learning paths have become key issues in enhancing learning outcomes. Current study primarily focuses on personalized recommendation systems based on big data and artificial intelligence (AI) algorithms. While these systems have achieved a certain degree of accuracy in recommending learners' interests and learning content, problems such as recommendation precision, dynamic adaptation to changing interests, and insufficient integration of diversified learning scenarios persist. Therefore, improving the adaptability of personalized learning systems through more intelligent and dynamic learning path optimization methods remains a pressing challenge in this field. Building on existing research, a personalized English learning interest point recommendation model based on the graph convolutional network (GCN) was proposed, and personalized learning paths were optimized by incorporating multidimensional contextual information. The GCN was used to uncover the relationships between learners and knowledge points, thus constructing a precise interest point recommendation mechanism. Additionally, learning paths were dynamically adjusted by considering learners' historical behaviors, learning progress, and situational context, offering a personalized learning experience. This study advances the development of personalized learning recommendation technologies and provides English learners with a more intelligent and precise learning path optimization solution.

KEYWORDS

personalized learning, English learning, graph convolutional network (GCN), interest point recommendation, learning path optimization, multidimensional contextual information

1 INTRODUCTION

With the ongoing advancement of educational reform, the application of collaborative innovation concepts in the mechanism of scientific research feeding back into

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teaching and talent development in universities has increasingly attracted attention. Higher education, as a crucial platform for talent cultivation and scientific research innovation, has promoted the enhancement of educational quality in recent years through strengthening the interaction and integration of research and teaching. Against this backdrop, the rapid development of IT, particularly the widespread adoption of mobile internet and smart devices, has ushered in an unprecedented transformation in the field of education. Traditional methods of English language learning are no longer sufficient to meet the increasingly personalized and diversified needs of modern learners, especially in the areas of learning path and content recommendation [1–4]. The application of mobile interaction technology has made personalized learning possible by analyzing learners' behaviors, interests, and learning progress, enabling the customization of suitable learning content and paths for each learner [5–9]. Consequently, how to leverage mobile interaction technology to enhance English learning outcomes has become a significant research direction in the field of educational technology.

Currently, research on personalized learning has encompassed various technologies and methods, including personalized recommendation systems based on big data analysis and artificial intelligence (AI) algorithms [10–12]. In the domain of English learning, the application of personalized recommendation models has made notable progress, allowing for the recommendation of appropriate learning materials based on learners' interests and proficiency, as well as providing real-time adjustments to learning paths. However, most existing personalized learning systems still face certain limitations, primarily in the recommendation accuracy of models, adaptability to dynamic changes in learners' interests, and the comprehensive consideration of diverse learning scenarios [13, 14]. Therefore, further research and exploration of more efficient and precise methods for optimizing personalized learning paths hold significant academic and practical value.

Despite the substantial body of research on personalized recommendations, most of these studies focus on the analysis of static data or simple content recommendation models, neglecting the dynamic changes in learners' interests and the long-term optimization of learning paths [15–20]. On one hand, traditional recommendation systems often rely on historical data from users, but they typically fail to capture and adjust for real-time changes in their interests. On the other hand, existing learning path optimization methods tend to rely heavily on a single-dimensional analysis and do not effectively integrate multidimensional contextual information, such as the learner's situation, emotions, and social interactions. As a result, the effectiveness and adaptability of recommendation systems remain insufficient. Therefore, the construction of a highly accurate and sustainably optimized personalized learning system has become an urgent problem in current study.

This study focuses on a personalized English learning recommendation model using graph convolutional network (GCN) and optimizing learning paths by integrating multidimensional contextual information. The GCN-based model improves the accuracy and relevance of interest point recommendations by analyzing relationships between learners and knowledge points. For learning path optimization, the study dynamically adjusts paths based on contextual data, such as learners' history, progress, and situational factors, to create a more personalized learning experience. The study combines deep learning with multidimensional data fusion to enhance adaptability and long-term optimization in personalized learning systems, ultimately providing more accurate and efficient recommendations and learning paths for English learners.

2 PERSONALIZED ENGLISH LEARNING RECOMMENDATION MODEL WITH MOBILE INTERACTION

Traditional personalized recommendation systems typically rely on the historical behavioral data of users. However, they often overlook the interrelationships between learners and the intrinsic connections between knowledge points. In mobile interactive learning environments, the behavioral data of learners are not confined to a single type of learning activity but instead present diversified interaction patterns, such as social interactions, real-time feedback, and situational changes. Consequently, a personalized English learning interest point recommendation model based on GCN was proposed in this study. GCN effectively utilizes graph-structured models to integrate multidimensional information regarding learners, learning content, and their interactive relationships into the recommendation system. This enhances the accuracy and adaptability of recommendations. For instance, by considering the similarity relationships between learners, the associations among learning content, and learners' varying levels of interest in different knowledge points, GCN can more flexibly and dynamically adjust the interest point recommendations for each learner, thereby enabling personalized learning path planning.

In traditional recommendation systems, interest point recommendations are usually based on a simple user-item interaction matrix, often neglecting the complex interrelationships between learners and learning content. In contrast, in mobile interactive learning environments, rich graph-structured relationships emerge between learners, learning content, learning behaviors, and learning states. GCN can represent both learners and learning content as nodes in a graph, while the interactions between learners and content are represented as edges, effectively capturing these complex relationships. After incorporating the attention mechanism, the model can not only account for direct relationships between learners and content but also weigh the learner's historical behaviors and interest changes. This allows the model to automatically learn which nodes and edges are more significant for recommendations, thereby enhancing the personalized accuracy of the recommendations. Furthermore, by integrating node features across different graph convolution layers, GCN can extract more useful features from multi-level and multidimensional information, further enhancing the model's expressive capability. This approach is adaptable to the continuously evolving learning interests and provides personalized interest point recommendations for learners in dynamic learning environments. The framework of the proposed model is illustrated in Figure 1.

The basic principle of the constructed model relies primarily on the advantages of GCN in processing graph-structured data. After introducing the attention mechanism, the model is capable of considering not only the direct relationships between learners and content but also weighting the learner's historical behaviors and interest changes. This enables the model to automatically learn which nodes and edges are more important for the recommendation, thereby enhancing the personalized accuracy of the recommendations. Moreover, by integrating node features across different graph convolution layers, GCN can extract more useful features from multi-level and multidimensional information, further improving the model's expressive power. To accommodate the training of large-scale graph data and to enhance the convergence speed and stability of the model, the sampling method from the graph sample and aggregation (GraphSAGE) was incorporated into the proposed model. Additionally, the model integrates techniques such as residual neural networks, normalization, and regularization. These methods not only improve the stability of the training process and reduce overfitting but also accelerate the convergence of the model.

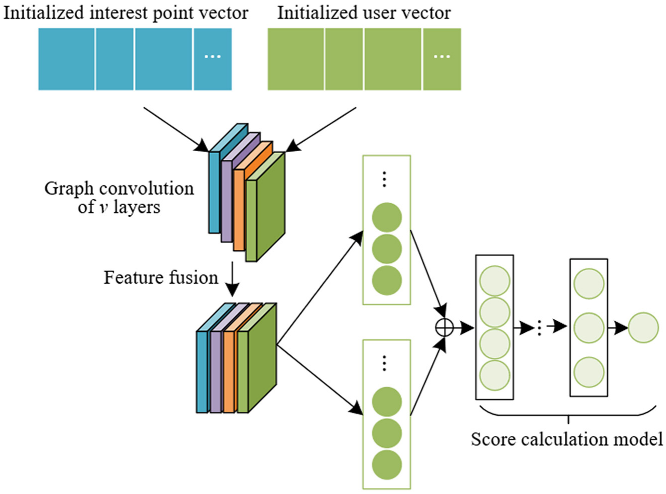


Fig. 1. Framework of the personalized English learning interest point recommendation model based on mobile interaction technology

2.1 Introduction of the attention mechanism

Unlike traditional GCN, the graph attention network (GAT) introduces an attention mechanism that allows the model to assign different weights to each node and its neighboring nodes during the learning process. This approach dynamically adjusts the importance of nodes based on their relationships and contextual information, thus improving the accuracy of the recommendation system. Drawing from the concept of GAT, the attention mechanism in this study first adjusts the weight of each node by calculating the similarity between learners and interest points, further optimizing the personalized interest point recommendation. When the relationship between a learner and an interest point is stronger, higher weights are assigned by the attention mechanism, whereas lower weights are assigned when the relationship is weaker. This enables the model to automatically identify changes in the learner's interests and preferences during the learning process.

Figure 2 illustrates the principle of similarity calculation. Specifically, the similarity computation within the model was performed by projecting, concatenating, and weighting the feature vectors of the user and interest points. In the similarity calculation for each learner node, the original feature vector of the user was projected onto the feature vector of the interest point. After obtaining a new representation, the user's feature vector was concatenated with the feature vectors of neighboring interest points, and the similarity between the learner and the interest point was then computed.

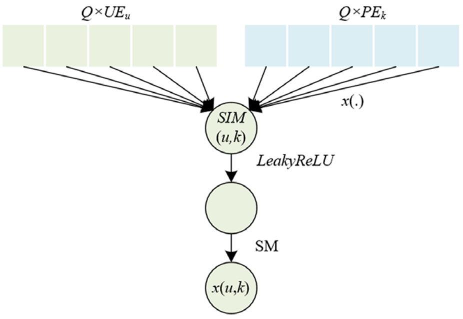


Fig. 2. Similarity calculation

This process integrates the user's historical behavior, interest changes, and contextual information, with the similarity values of all adjacent nodes being normalized using the SoftMax function, resulting in the final similarity weights. Let the user vector and the graph convolution vector before the graph convolution be denoted as UE and PE, respectively. The user vector is represented as an $i \times j$ matrix, and the interest point vector is represented as an $o \times j$ matrix, where i denotes the number of users, o denotes the number of interest points, and j represents the dimension of the feature vectors for both users and interest points. Let the original feature vector of user u be denoted as UE_u, and the set of all its neighboring nodes be denoted as V_u. The original feature vector of interest point k is denoted as PE_u, and the concatenation of the two vectors is represented by $||$. The concatenated vector is then projected into a scalar similarity value, represented by the function β (). The similarity between user u and interest point k can thus be calculated as follows:

$$SIM_{uk} = x(Q \times UE_u \| Q \times PE_k), PE_k \in V_u \tag{1}$$

The formula for calculating the normalized similarity coefficient is as follows:

$$x_{uk} = \frac{\exp\left(LR(SIM_{uk})\right)}{\sum_{j \in V_u} \exp\left(LR(SIM_{uk})\right)} \tag{2}$$

In the recommendation model, the core task of the convolutional aggregation operation is to update the user's feature representation by aggregating information from the learner and neighboring nodes. Specifically, the model first aggregates the information of neighboring nodes based on the similarity coefficients calculated in the previous step, thereby obtaining a more accurate representation of the user's interests. This process is accomplished through a convolution operation applied to the features of each user node and its neighboring nodes. In the graph convolution operation, the features of the user node UE_u and the neighboring interest point nodes are aggregated through a weighted sum. The result is then transformed non-linearly using an activation function δ (), which produces the updated user feature. This operation captures the relationship between the user and interest points while also considering the learner's interactions with other learning content, allowing the model to provide more personalized and accurate recommendations for the learner's interests in a dynamic mobile interactive learning environment.

$$UE_u = \delta\left(\sum_{k \in V_u} x_{uk} QPE_k\right) \tag{3}$$

To further improve the model's performance, a multi-head attention mechanism was introduced in this study to address the overfitting issues that may arise from a single-head attention mechanism. In a single attention mechanism, the weights tend to be concentrated on a few important interest points, which can lead to bias during training. Therefore, a multi-head attention mechanism was employed, where multiple independent attention heads are combined, with each attention head learning different aspects of the data, thus preventing excessive reliance on specific interest points. Each attention head computes a weighted aggregation result, and the corresponding vectors are added dimensionally, resulting in the updated user feature. This method not only avoids the overfitting problem associated with a single attention head but also captures the diverse relationships between the user and interest points in higher-dimensional spaces. To enhance training efficiency and reduce the model size, dimension-wise addition was chosen over vector concatenation, which effectively reduces the computational load and accelerates the training process. Let the number of attention heads in the multi-head attention mechanism be denoted as *J*, and let vector concatenation or dimensional addition be denoted as *U*. The formula is then given by:

$$UE_u = \Big\|_{|j=1|}^{J} \delta\left(\sum\nolimits_{k \in V_u} x_{uk} Q \times PE_k\right) \tag{4}$$

2.2 Multidimensional feature fusion

The multidimensional feature fusion principle employed in the model effectively integrates the complex relationships between the learner and learning content, thereby enhancing model performance. The key advantage of multidimensional feature fusion lies in its ability to combine both the low-level graph convolution features, which capture the detailed structural characteristics, and the high-level graph convolution features, which extract global characteristics. Specifically, low-level graph convolutions capture detailed information about the learner's direct interest point neighbors, including the user's current interest tendencies, learning behaviors, and immediate needs. In contrast, high-level graph convolutions are capable of extracting highly generalized features from the entire graph, capturing macroscopic interest patterns and global learning trends formed during long-term interactions. More specifically, the user features are updated using function *CV_I*, based on the features of their neighboring interest points, while the interest point features are updated using function *CV_O*, based on the features of their neighboring users. These two graph convolution functions work together by aggregating information from neighboring nodes to update node features, ensuring that each node can fully absorb valuable information from its neighbors. As the network layers increase, the graph convolution functions are gradually able to integrate deeper-level information, transitioning from local features to global features. Let the input of the first-layer graph convolution be the raw user and interest point vectors UE^0 and PE^0, respectively. The input of the *u*-th layer graph convolution is the user and interest point vectors UE^{u-1} and PE^{u-1}, obtained from the output of the (*u-m*)-th layer graph convolution. The formula is given by:

$$\begin{aligned} &UE^1 = CV\_I(UE^0, PE^0), PE^1 = CV\_O(PE^0, UE^0), \\ &UE^u = CV\_I(UE^{u-1}, PE^{u-1}), PE^u = CV\_O(PE^{u-1}, UE^{u-1}) \end{aligned} \tag{5}$$

To further improve model performance, a *K*-layer GCN was employed, where the features of each layer are fused with the features of the previous layer. This ensures that the final node representations comprehensively account for structural features from different layers of the graph. The feature fusion formula for a *J*-layer GCN is given by:

$$UE = \sum_{u=1}^{J} UE^u, PE = \sum_{u=1}^{J} PE^u \tag{6}$$

2.3 Residual neural network

As the number of graph convolution layers increases, the feature representations in the model typically become more abstract. In deep networks, information may gradually be lost during the propagation process across multiple convolutional layers, leading to a decline in performance. By incorporating residual connections into the convolutional network, the model can bypass certain layers and directly fuse low-level features with high-level features, ensuring that information is not lost during upward propagation. Specifically, during the feature fusion process of users and interest points, the residual connections allow the features outputted by low-level graph convolutions to be directly passed to the features from higher-level GCNs, thereby preventing challenges such as vanishing gradients or information loss in deep networks. Furthermore, the introduction of residual neural networks not only resolves the vanishing gradient problem encountered in deep networks but also accelerates the convergence speed of the model to some extent. In traditional neural networks, as the number of layers increases, the training process can become very slow, with a tendency to fall into local optima. By skipping certain layers, residual networks ensure that low-level features are directly transmitted to higher layers, thereby accelerating the flow of information and enabling the model to learn features more efficiently.

2.4 Training methods

In traditional GCN training, handling large-scale graph data often leads to slow training speeds and difficulties in effective convergence, especially when user-interest point interaction data is sparse, making it challenging for the model to capture sufficient information. To address this challenge, the principle of the GraphSage-based sampling method was adopted, where the graph is reduced and sampled using graph sampling techniques. During each training iteration, user nodes were first randomly sampled, and then interest point nodes adjacent to these sampled user nodes were randomly selected to form a new, smaller graph. For this new graph, graph convolution operations were performed to update the feature representations of users and interest points.

Furthermore, to mitigate the training difficulties caused by data sparsity, the label sampling training method was employed. In this process, the selection and sampling of positive and negative samples are crucial. Specifically, positive sampling selects records of interactions between users and interest points as positive samples, ensuring that the model learns the true preferences of users towards certain interest points. Negative sampling, on the other hand, randomly selects a certain number of negative samples from interest points with which the user has not interacted, helping the model distinguish irrelevant interest points, thereby improving the accuracy of recommendations. The ratio of positive to negative samples was adjusted according to the characteristics of different datasets, ensuring that the model can fully learn the distinction between positive and negative samples during training, thus preventing overfitting.

3 PERSONALIZED ENGLISH LEARNING PATH OPTIMIZATION INTEGRATING MULTIDIMENSIONAL CONTEXTUAL INFORMATION

In traditional learning path recommendation systems, learners' immediate needs, contextual factors, and external disruptions that arise during the learning process are often overlooked. However, in the application of mobile interactive technologies, learners do not rely solely on fixed teaching content and learning paths; instead, their learning needs dynamically evolve as the learning process, environment, and interaction methods change. Additionally, mobile interactive technologies typically enable learners to engage in learning anytime and anywhere, highlighting the fragmented and diverse nature of the learning process. For instance, learners may use different devices to access learning materials, and each device's usage scenario and interaction mode can influence the selection of their learning path. For these reasons, this study integrates multidimensional contextual information into the learning path optimization process, allowing the system to adjust learning paths in real-time based on several factors, including the learner's current progress, interest points, device usage, and interactive feedback, thus providing personalized learning recommendations.

3.1 Integration of textual information

The optimization of learning paths relies not only on learners' historical learning behaviors but also on the semantic information of the learning content. In mobile interactive learning environments, learners interact with various types of learning content, such as comments, learning notes, or diverse course materials. These textual resources contain in-depth understanding and contextual feedback on the learning content, helping the model identify learners' interest points and needs related to specific learning resources. By utilizing the Doc2Vec model, learning resources enriched with textual data, such as course introductions, learning notes, comments, and others, can be transformed into vector representations containing semantic information. These representations are then integrated with the learners' behavior data, forming a semantic connection between the learner and the learning content. This approach enables the system to better understand the learner's preferences for specific topics or knowledge points, thereby recommending more personalized and relevant learning paths.

In the process of personalized English learning path optimization, the construction of textual vectors is carried out by learning the embedding vectors of each paragraph or learning resource, which are then combined with learners' behavior data to generate personalized learning paths. In this model, each learning resource is treated as a "paragraph," and the interaction between each learner and these resources provides the model with the semantic association between the learner and the resources. Specifically, the Doc2Vec model was first applied to train learning resources containing textual information, obtaining paragraph vector representations for these resources. These vectors are capable of capturing the semantic information of the learning content, such as lexical associations, topic relevance, and contextual meanings. Subsequently, these paragraph vectors were combined with the learners' interest point vectors to form a comprehensive learner vector, which represents the learner's interests and needs.

Learning resources on the platform is typically tagged with labels that describe the resource's theme, difficulty, category, and so on. For each user, interactions with these labels reflect their preferences and needs concerning specific learning content. In this context, the user's textual vector can be obtained by calculating the weighted sum of the interactions with the labels. Suppose the learning record of user X contains multiple labels $[LA_{X1}, LA_{X2}, \ldots, LA_{Xv}]$, with each label having a different frequency of occurrence, denoted as $[Z_{X1}, Z_{X2}, \ldots, X_{Xv}]$. Different weights can be assigned to each label according to its frequency. For instance, if a label frequently appears in the user's learning record, its weight will be relatively small, indicating a lower influence on the user. In contrast, labels with lower frequencies are assigned higher weights. By applying this weighted sum approach, the system can more accurately capture the user's interest points and learning preferences, thereby recommending the most suitable learning content and paths. The following formula provides the calculation of the weight for label LA_{X1} in the learning record of the user X:

$$Q_{X1} = \frac{\frac{1}{Z_{X1}}}{\sum_{u=1}^{v} \frac{1}{Z_{Xu}}} \tag{7}$$

3.2 Integration of other information

In the optimization of personalized learning paths, unsupervised contextual information cannot be overlooked, as it reflects the learner's needs in various situations. For example, when a learner browses multiple related courses under a particular topic but does not engage in deep learning, it may be due to certain details or difficulty levels within the topic that have not been accurately captured. The variational autoencoder (VAE) model encodes these unlabeled contextual data to generate a low-dimensional latent space, where the latent vectors can encapsulate various potential information such as learner interests, learning habits, and emotional feedback. Figure 3 presents the VAE model framework.

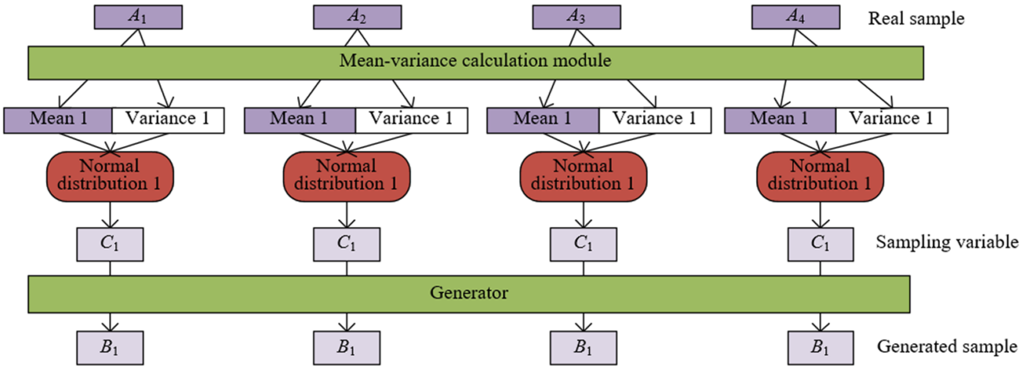


Fig. 3. VAE model framework

By minimizing reconstruction error and kullback-leibler (KL) divergence, the VAE not only ensures that the distribution of contextual information in the latent space follows a normal distribution but also helps the system identify and learn hidden associations and potential interests that may not have been explicitly observed. This enables the generation of more representative feature vectors for personalized recommendations. The loss function of the VAE model is as follows:

$$LOSS = MSE(A,B) + KL\left(V(\omega_1,\delta_1^2),V(0,1)\right) \tag{8}$$

Assuming that the mean and variance output by the mean-variance calculation module is represented by ω_1 and δ_1, the detailed formula for the KL divergence is given as:

$$KL\left(V(\omega_1,\delta_1^2),V(0,1)\right) = \left(\omega_1^2 + \delta_1^2 - 2\log(\delta_1) - 1\right)/2 \tag{9}$$

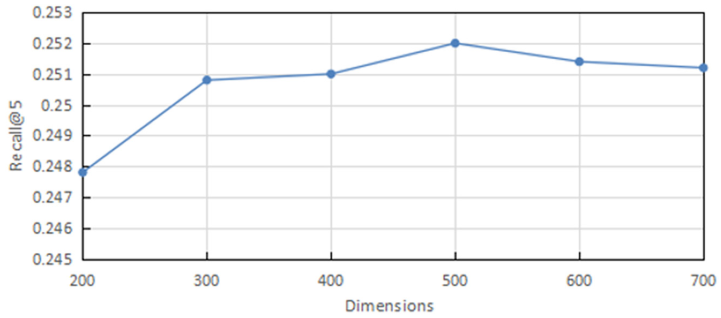
4 EXPERIMENTAL RESULTS AND ANALYSIS

Based on the experimental results in Table 1, the proposed personalized English learning interest point recommendation model, based on GCN, demonstrates significant advantages across multiple evaluation metrics. Specifically, the model outperforms other deep learning models, such as the long short-term memory (LSTM), the autoencoder-based recommendation (AutoRec), the time-aware LTSM (Time-LSTM), the neural matrix factorization (NeuMF), the convolutional neural network for text (Text CNN), the self-attentive sequential recommendation (SASRec), and the spatio-temporal attention-based recommendation (STAMP), on both the training and testing sets. For instance, the $R@5$ metric on the training set increases from 0.0985 for LSTM to 0.2452 for the proposed model, yielding an improvement rate of 32.12%. On the testing set, the $R@5$ increases from 0.2215 for LSTM to 0.3356, with an improvement rate of 4.23%. Furthermore, the model also shows significant improvements in $N@5$, with increases of 37.26% on the training set and 6.15% on the testing set. These results indicate that the GCN-based model is more effective at capturing the relationships between learners and the inherent connections between knowledge points, thereby enhancing the accuracy and relevance of personalized recommendations.

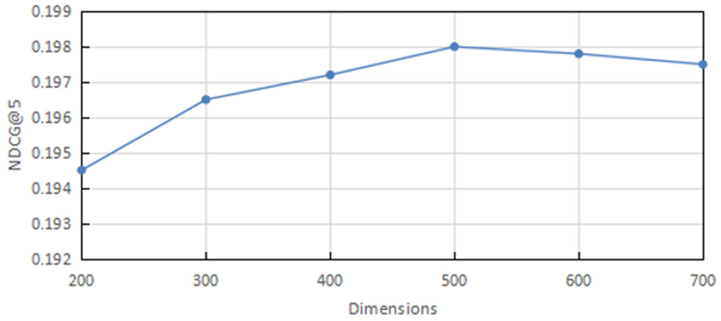
Table 1. Comparison of the performance of the proposed model and other deep learning models in personalized English learning interest point recommendation

Model	Training Set				Testing Set			
	$R@5$	$R@10$	$N@5$	$N@10$	$R@5$	$R@10$	$N@5$	$N@10$
LSTM	0.0985	0.1123	0.0725	0.0815	0.2215	0.2562	0.1452	0.1652
AutoRec	0.1325	0.1562	0.0874	0.1124	0.2152	0.2845	0.1562	0.1756
Time-LSTM	0.1456	0.1785	0.1252	0.1236	0.2756	0.3526	0.2236	0.2236
NeuMF	0.1652	0.2235	0.1123	0.1325	0.2653	0.3541	0.1895	0.2215
Text CNN	0.1235	0.1754	0.1256	0.1256	0.3256	0.3789	0.2236	0.2456
SASRec	0.1523	0.2152	0.1125	0.1225	0.2652	0.3652	0.1852	0.2132
STAMP	0.1895	0.2365	0.1236	0.1652	0.3125	0.4123	0.2236	0.2465
Proposed model	0.2452	0.3125	0.1866	0.2236	0.3356	0.4215	0.2644	0.2756
Improvement rate	32.12%	22.36%	37.26%	33.56%	4.23%	3.89%	6.15%	4.49%

As shown in the data presented in Figure 4, the proposed personalized English learning interest point recommendation model, based on GCN, demonstrates stable and outstanding performance on the training set in terms of the $R@5$ and $N@5$ metrics. The $R@5$ results show a slight improvement with the increase in feature dimensions, gradually increasing from 0.2478 at 200 dimensions to 0.2512 at 700 dimensions. The overall increase is relatively steady, with the $R@5$ value approaching stability as the dimensionality increases, indicating that higher-dimensional feature spaces offer more consistent performance in capturing learners' interest points. Additionally, a similar trend is observed for the $N@5$ metric, which increases steadily from 0.1945 at 200 dimensions to 0.1975 at 700 dimensions. This consistent growth further validates that the model's ranking quality of recommended results improves as the feature dimensions increase.



a) *R*@5



b) *N*@5

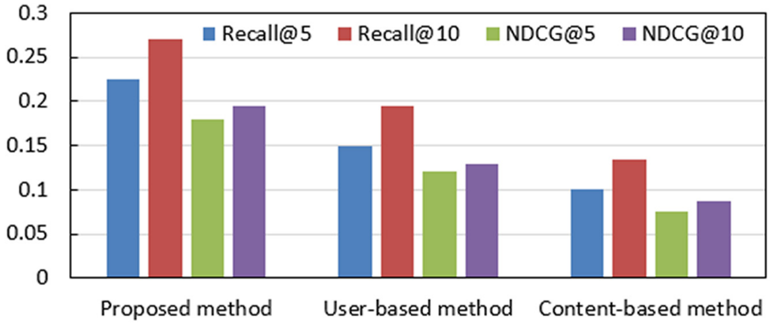
Fig. 4. Performance of the proposed model in terms of *R*@5 and *N*@5 on the training set

Based on the data presented in Table 2, the impact of each key component on the model's performance can be observed. Firstly, the full model demonstrates significant improvements on both the training and testing sets, particularly in the *R*@5 and *R*@10 metrics. For instance, *R*@5 in the training set increases from 0.1895 (without the attention mechanism) to 0.2456, showing a 29.6% improvement. On the testing set, *R*@5 rises from 0.3125 to 0.3362, an improvement of 7.6%. Furthermore, the full model significantly outperforms configurations that exclude additional information integration or multi-dimensional feature fusion, especially on the *N*@5 metric in the testing set, showing stronger recommendation accuracy and ranking ability. A deeper analysis reveals that the removal of any key component results in a decrease in model performance, with a particularly noticeable drop in recommendation accuracy and relevance when the graph sampling, residual neural network, or attention mechanism are omitted. The most significant decrease can be observed when textual information is not incorporated, with both *R*@5 and *N*@5 metrics experiencing a substantial drop. This highlights the essential role of textual information in the recommendation of learning interest points.

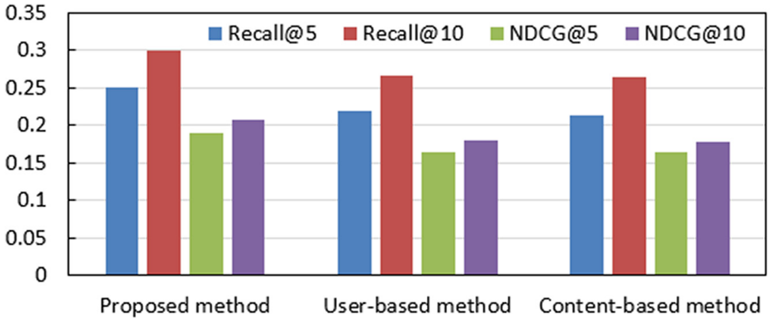
Table 2. Performance comparison of key components in the proposed model

Model	Training Set				Testing Set			
	R@5	*R*@10	*N*@5	*N*@10	*R*@5	*R*@10	*N*@5	*N*@10
No attention mechanism	0.1895	0.2369	0.1325	0.1452	0.3125	0.4125	0.2315	0.2561
No multi-dimensional feature fusion	0.1789	0.2451	0.1362	0.1562	0.3265	0.4235	0.2235	0.2632
No residual neural network	0.2236	0.2789	0.1789	0.1895	0.3124	0.3895	0.2362	0.2548
No graph sampling	0.2254	0.2752	0.1745	0.1945	0.3248	0.4152	0.2451	0.2652
No textual information integration	0.1562	0.2235	0.1241	0.1352	0.3125	0.3895	0.2268	0.2326
No additional information integration	0.2156	0.2561	0.1623	0.1874	0.2325	0.2895	0.1895	0.2152
Full model	0.2456	0.3125	0.1789	0.2236	0.3362	0.4125	0.2365	0.2789

As shown in the data presented in Figure 5, the proposed personalized English learning interest point recommendation method, based on GCN, outperforms traditional user- and content-based recommendation methods on both the training and testing sets. Specifically, on the training set, the proposed method achieves $R@5$ and $R@10$ values of 0.225 and 0.270, respectively, while the user- and content-based methods achieve $R@5$ values of 0.150 and 0.100 and $R@10$ values of 0.195 and 0.135, demonstrating a significant advantage.



a) Training Set



b) Testing Set

Fig. 5. Comparison of the proposed model with other recommendation methods in personalized English learning interest point recommendation performance

On the testing set, the proposed method continues to maintain its lead, with $R@5$ and $R@10$ values of 0.250 and 0.300, respectively, compared to the user- and content-based methods. Additionally, the proposed method shows a marked improvement in terms of $N@5$ and $N@10$ metrics. On the training set, $N@5$ and $N@10$ for the proposed method are 0.180 and 0.195, whereas the user- and content-based methods only achieve 0.120, 0.075, 0.130, and 0.088, respectively. On the testing set, the proposed method achieves $N@5$ and $N@10$ values of 0.190 and 0.208, again outperforming the user- and content-based methods.

5 CONCLUSION

A personalized English learning interest point recommendation model based on GCN was proposed in this study, which significantly improves the accuracy and personalization of the recommendation system by deeply exploring the relationship network among learners and the intrinsic connections between knowledge points. Compared to traditional user- or content-based recommendation methods, the GCN model demonstrates superior performance in metrics such as $R@5$, $R@10$, $N@5$, and $N@10$, with particularly notable advantages in recommendation relevance and ranking quality. Furthermore, a strategy for optimizing the learning path by integrating multidimensional contextual information (e.g., learner history, learning progress, and contextual data) was proposed, enhancing the personalization and intelligence of the learning experience. This strategy allows the dynamic adjustment of the learning path according to the actual needs of the learner, thus better supporting personalized English learning.

Despite the promising results achieved in personalized recommendation and learning path optimization by the proposed model, certain limitations remain. First, the model relies heavily on GCN, and its performance may be influenced by the construction of the graph structure and the quality of training data. Challenges may arise in terms of computational efficiency and storage resources when dealing with large-scale learners and knowledge points. Second, although the integration of multidimensional contextual information improves the model's personalization, accurately capturing and processing contextual data in diverse situations remains an open issue in practical applications. Additionally, when modeling the long-term evolution of learner behavior, there may be potential issues with lag or overfitting. Future research could explore the following directions: first, further optimization of the efficiency of GCN, particularly for large-scale datasets; second, strengthening the multimodal integration of contextual information, considering the impact of learning environments, situations, and emotional factors; and third, exploring the model's ability to engage in continuous learning and adaptive adjustment, allowing it to better accommodate the evolving needs of learners over time.

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