

PAPER

The Impact of Mobile Interactive Technology on International Chinese Learning: A Case Study of AI-Driven Applications

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With the rapid advancement of mobile internet technology and artificial intelligence (AI), mobile interactive technology has been increasingly applied to international Chinese learning. By leveraging smart devices and online platforms, learners can overcome the limitations of traditional classroom teaching, enabling more flexible and personalized learning experiences. However, existing research has yet to fully consider key factors such as individual learner differences, interaction dynamics, and learning behavior prediction in assessing the effectiveness of mobile interactive learning for Chinese language acquisition. Consequently, enhancing learning outcomes and prediction accuracy through advanced AI-driven approaches has become a critical issue in the field of Chinese language education. Most current studies focus on specific tools or teaching models, often relying on localized data analysis while lacking a comprehensive exploration of learner behavior dynamics, individual preferences, and interaction patterns. To address this gap, this study proposes a predictive model for mobile interactive learning among international Chinese learners, integrating a hypergraph attention mechanism (HGAM) and a graph convolutional network (GCN). By modeling learner interactions, behavioral characteristics, and preferences, this study aims to improve the accuracy of learning outcome predictions and provide theoretical foundations for personalized and intelligent teaching strategies. The novelty of this study lies in its pioneering integration of graph neural networks with mobile interactive learning, surpassing the limitations of traditional teaching models and contributing valuable insights to both academic research and practical applications.

KEYWORDS

mobile interactive technology, international Chinese learning, artificial intelligence (AI), hypergraph attention mechanism (HGAM), graph convolutional network (GCN), learning prediction

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1 INTRODUCTION

With the rapid development of information technology, especially the continuous progress of artificial intelligence (AI) technology, mobile internet has become an important tool in the global education field [1–4]. Reference [5] mentions that, particularly in the learning of Chinese as a second language, mobile interactive technology is changing traditional learning models due to its convenience and efficiency. International Chinese learners engage in online learning through smart devices, not only overcoming geographical and time constraints but also providing a more personalized and interactive learning experience [6–9]. The application of mobile interactive technology brings new opportunities to Chinese language education while also posing new challenges to learning effectiveness and learning methods. Meanwhile, how to effectively utilize these technologies to improve the learning outcomes of international Chinese learners has become one of the hot topics in current research.

Although a large number of studies have involved the application of mobile learning and AI in language learning, the existing research methods still have certain limitations. First, many studies overly focus on local data analysis and overlook the complex interaction relationships among learners [10–13]. Second, existing learning prediction models often fail to fully consider learners' global preferences and the dynamic changes in learning behavior, resulting in weak accuracy and generalization ability in practical applications [14–17]. Third, current research lacks the effective integration of AI algorithms, particularly in combining advanced graph neural networks with learner interaction data to enhance the accuracy and effectiveness of learning prediction [18]. Therefore, this study aims to propose a more comprehensive and accurate international Chinese learner behavior prediction model by integrating the hypergraph attention mechanism (HGAM) and graph convolutional network (GCN) to fill the gap in existing research.

This study is mainly divided into two parts. First, the paper will explore how to integrate the HGAM with the GCN for mobile interactive learning prediction among international Chinese learners. This part will focus on the construction of the model and the optimization of algorithms, with experimental data used to verify its effectiveness. Second, this study will investigate the interaction relationships among international Chinese learners, exploring learners' global preferences and mobile interactive learning prediction methods. This part of the research will help to gain a deeper understanding of the dynamic changes in learner behavior and provide theoretical support and technical pathways for future personalized teaching and intelligent learning in Chinese language education. This study not only offers new ideas for improving the learning outcomes of Chinese learners but also provides valuable references for the application of AI in the field of educational technology.

2 PROBLEM DESCRIPTION OF INTERNATIONAL CHINESE MOBILE INTERACTIVE LEARNING PREDICTION

With the continuous development of AI technology, traditional learning prediction methods have gradually become unable to meet the diverse and complex learning needs. Particularly in the mobile interactive learning environment, the interaction relationships among learners, the dynamic changes in learning behavior, and the differences in individual preferences pose great challenges to learner behavior prediction. Therefore, this study aims to construct an innovative mobile interactive learning prediction model by integrating the HGAM and GCN to accurately predict the interactive behavior of international Chinese learners at a future moment.

The core issue of this study is how to model the mobile interaction network graph (CM) and interaction hypergraph (GD) of international Chinese learners to predict the probability of learners engaging in mobile interactions at future time points. To address this, this study proposes a time-stamped cascade graph sequence model, where the cascade graph sequence of each tweet message on a mobile learning platform is represented as $Z_u(s) = [(I_u(s_1), (R_u(s_1))), \dots, (I_u(s_l), R_u(s_l))]$, where $I_u(s_k)$ is the set of international Chinese learners and $R_u(s_k)$ is the set of edges. The state of each tweet at time s_k can be represented by the adjacency matrix $X_u^s = \{x_u^{s1}, x_u^{s2}, \dots, x_u^{sl-1}\}$. Through this model, this study aims to capture the interaction patterns of learners within tweet cascades and make predictions of future mobile interaction behaviors through precise modeling of learner behavior. Figures 1 and 2 illustrate the working principles of the mobile interaction network graph and interaction hypergraph in the prediction model.

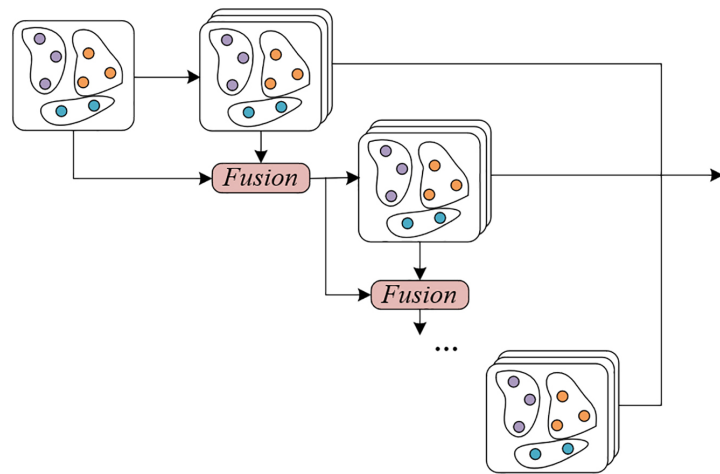


Fig. 1. Schematic diagram of the working principle of the interactive hypergraph in the prediction model

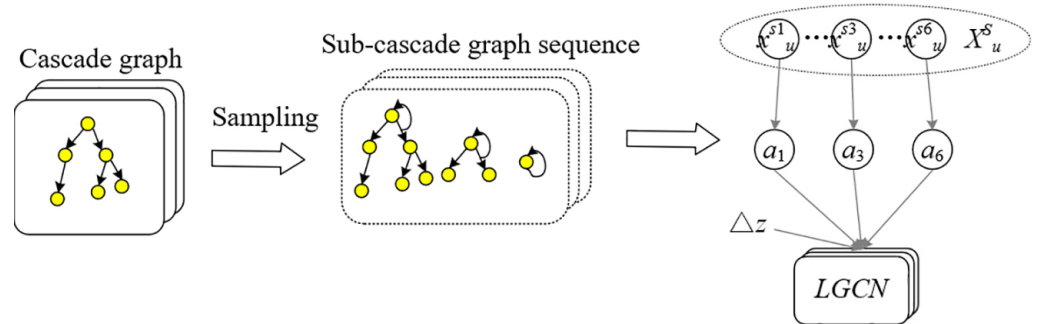


Fig. 2. Schematic diagram of the working principle of the mobile interactive network graph in the prediction model

Another challenge in this study is how to use the interactive hypergraph GD to capture the complex interaction relationships among learners. The interactive hypergraph consists of a series of timestamped subsets, where each subset connects relevant learners through hyperedges. By introducing interactive hypergraph modeling, this study can reveal the dynamic interaction relationships among learners and predict learner behavior at each moment accordingly. In the model, the node-hyperedge relationships in each hypergraph are unique, meaning that within a certain time interval, the connection between international Chinese learner i_u and hyperedge r_l exists only in the hypergraph γ^s at the current timestamp. This unique hypergraph structure effectively characterizes the evolution of learner behavior and

provides a more accurate basis for predicting learners' mobile interactive behavior at future moments.

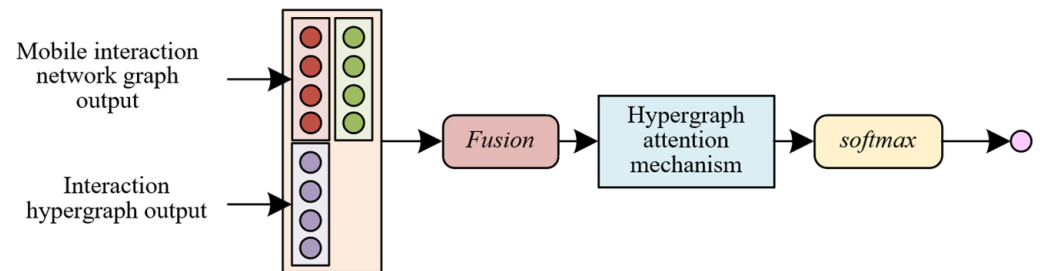


Fig. 3. Overall framework of the prediction model

Figure 3 presents the overall framework of the prediction model. The proposed mobile interactive prediction model is not limited to the application of the GCN but also integrates the HGAM to enhance the model's representation capability. Specifically, by sampling the cascading relationships among international Chinese learners, the model introduces the cascading Δz Laplacian operator and employs the localized graph convolutional network (LGCN) to learn learner interaction features in cascading sequences. This process helps extract complex relationships among learners and model their behavior. Finally, the model inputs these learned features into the multi-head attention mechanism for further processing. By calculating the probability of each learner being influenced by mobile interaction at a future moment, the model predicts which learners will participate in interactions in the future. By outputting the international Chinese learners with the highest probability of being influenced by mobile interaction, the model can effectively predict the next potentially influenced learner and provide a basis for personalized teaching and intelligent learning.

3 CONSTRUCTION OF THE INTERNATIONAL CHINESE MOBILE INTERACTIVE LEARNING PREDICTION MODEL

3.1 Learning of social relationships

The mobile interactive relationship graph CM of international Chinese learners is essentially a dynamic, directed graph network whose structure continuously evolves over time. At each timestamp s_k , the interaction relationships of learners can be represented by a cascading graph sequence: $Z_u(s) = [(I_u(s_1), (R_u(s_1))), \dots, (I_u(s_l), R_u(s_l))]$. Each tweet or interactive event can be regarded as a propagation dynamic at a timestamp. To further analyze these interactive relationships, we sample these cascading graphs to construct a sub-cascading graph sequence $H_u^s = \{h_u^{s1}, h_u^{s2}, \dots, h_i^{sl-1}\}$, storing them in the form of an adjacency matrix. This allows us to capture the interaction relationships among learners and the directionality of their interactions.

Based on the principle of "like attracts like," we hypothesize that learners with similar interests or behaviors are more likely to form interactions, and these interactions exhibit certain temporal and structural characteristics. To explain this interactive behavior, we introduce the cascading Δz Laplacian operator as an important tool for capturing homogeneity among international Chinese learners and their influence in interactions. The cascading Laplacian operator, by weighting the neighbor relationships of each node, can reveal the intensity and patterns of learner interactions,

thereby capturing the common characteristics and potential influence of learners in mobile interactions. Specifically, the Laplacian operator smooths each node in the graph, reducing noise effects in the graph and revealing the global dependency of learner behavior. The convolution operation on a single cascading signal A can be expressed as:

$$b = h_\phi * H_a = h'_\phi(M)a = \sum \phi'_j S_j(\tilde{\Delta}z) \tag{1}$$

Where, the scaled Laplacian function is given by:

$$\tilde{\Delta}z = \frac{2}{\eta_{MAX}} \Delta z - U_v \tag{2}$$

For a directed graph representing the mobile interaction relationships of international Chinese learners, in order to capture the special structures and directional characteristics of different cascades, a dual Laplacian operator is introduced. Specifically, assuming the transition probability matrix is denoted by O_z , the dual Laplacian operator by ε , and the initial probability by β , the calculation formulas are:

$$\varepsilon = \Theta^{\frac{1}{2}}(U - O)\Theta^{-\frac{1}{2}}, O_z = (1 - \beta)\frac{R}{V} + \beta(F^{-1}Q), \Delta z = \Theta^{\frac{1}{2}}(U - O_z)\Theta^{-\frac{1}{2}} \tag{3}$$

In the above formulas, $F^{-1}Q$ is used to ensure that no position in O_z is zero.

After constructing the sub-cascading graph sequence and the Laplacian matrix, we input this data into the GCN (LGCN). The GCN performs local convolution operations on graph data, efficiently learning structural dependencies among nodes and capturing complex interaction patterns among learners. In this model, we replace the traditional dense matrix Q multiplication with graph convolution, fully utilizing the adjacency information in the graph structure, thereby enhancing the model's ability to learn interactive relationships among learners. At the same time, with the integration of the HGAM, the model can flexibly focus on the importance of different learners and interaction relationships. With the help of the multi-head attention mechanism, we can weigh the influence of each learner, thereby achieving accurate prediction of different learners' roles in mobile interactions. Specifically, let $*H$ represent graph convolution and the cascading graph sequence signals be $X_u^s = \{x_u^{s1}, x_u^{s2}, \dots, x_u^{sl-1}\}$, then the calculation formulas are:

$$\begin{aligned} u_s &= \delta(Q_u * HA_s + I_u * Hg_{s-1} + N_u \otimes z_{s-1} + y_u) \\ d_s &= \delta(Q_d * HA_s + I_d * Hg_{s-1} + N_d \otimes z_{s-1} + y_d) \\ p_s &= \delta(Q_p * HA_s + I_p * Hg_{s-1} + N_p \otimes z_s + y_p) \end{aligned} \tag{4}$$

Assuming the hyperbolic tangent function is represented by $\tanh(\cdot)$, and the inner product by \otimes , further, using $Q_u * HA_s$ to represent the graph convolution of signal A_s , and replacing the existing memory unit z_s with a new unit, we have:

$$z_s = d_s \otimes z_{s-1} + u_s \otimes \tanh(Q_z * HA_s + I_z Hg_{s-1} + y_z) \tag{5}$$

Then, updating the hidden state gives:

$$g_s = p_s \otimes \tanh(z_s) \tag{6}$$

3.2 Global preference learning

Traditional GCN and graph attention networks (GAT) can capture local information in graph structures, but they still have limitations in capturing complex global preferences across time periods and nodes. To solve this problem, we propose mapping the cascading interaction information of international Chinese learners onto a diffusion hypergraph. In each time period, the hypergraph contains interaction information among learners, which is represented through hyperedges in the hypergraph. Each hyperedge connects a group of nodes that share similar interaction characteristics, and the root node of the hyperedge reflects the core content of the interaction in that time period. Therefore, the design of the hypergraph not only enhances the understanding of cross-time interaction patterns but also captures changes in learners' interests and behavioral preferences through the aggregation of hyperedges.

Based on the hypergraph, we further introduce the hypergraph attention network (HGAT), which calculates the attention score β_{uk}^s between the root node and other nodes to measure the importance of different learners' interactions within a specific time period. These attention scores help the model selectively focus on the most critical nodes for preference changes in the current time period, thereby transmitting information between nodes and updating node representations. On each hyperedge r_u^s , by aggregating the representations $a_{u,s}$ of all connected nodes i_u , we obtain the hyperedge representation $p_{k,s}$. Furthermore, these hyperedge representations are aggregated into the node representations. In this way, the HGAT can effectively capture learners' short-term interests and interaction preferences while preserving the key information of the hyperedge root node, thus enhancing the understanding of learners' behavior in a specific time period. Figure 4 illustrates the global preference learning process of learners. The specific formula is as follows:

$$\beta_{uk}^s = \frac{\exp(-DIS(Q_1 a_{u,a}^m, Q_1 e_k^m))}{\sum_{i_u^s \in r_k^s} \exp(-DIS(Q_1 a_{o,s}^m, Q_1 e_k^m))} \tag{7}$$

$$p_{k,s}^{m+1} = \delta \left(\sum_{i_u^s \in r_k^s} \beta_{uk}^s Q_1 a_{u,s}^m \right)$$

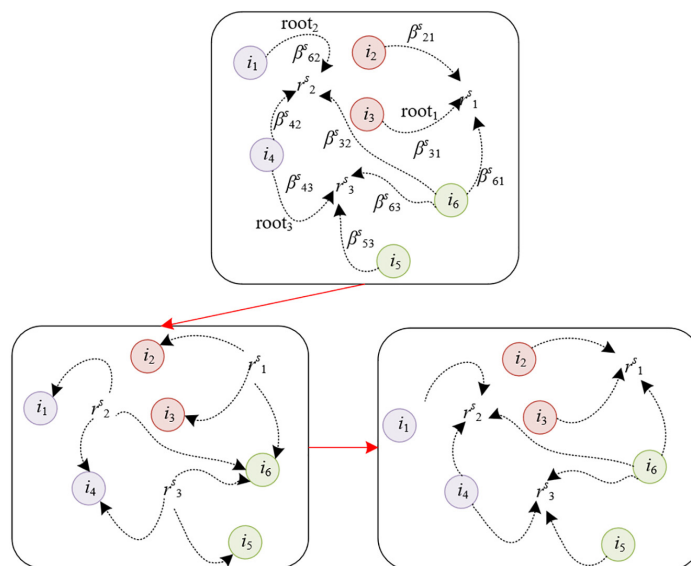


Fig. 4. The global preference learning process of learners

Assuming that the weights of all hyperedges are equal, in the s -th time interval, the representation of international Chinese learners' nodes, aggregated over all hyperedges, is given by:

$$a_{u,s}^{m+1} = \delta \left(\sum_{k \in \mathcal{Y}_u^s} Q_2 p_{k,s}^{m+1} \right) \tag{8}$$

By using the embedding vectors of international Chinese learners to update the hyperedge representations $p_{k,s}^{m+1}$, the connections between hyperedges can be further captured. The formula is as follows:

$$p_{k,s}^{m+1} = \delta \left(\sum_{u \in \mathcal{I}_k^s} \beta_{uk}^s Q_3 a_{u,s}^{m+1} \right) \tag{9}$$

However, since the weights of all hyperedges are equal and the interaction information within each time interval only reflects short-term preference changes, the model may not capture long-term global preferences solely through the HGAT. To address this limitation, we design a gating strategy to sequentially fuse the learner representations from different time periods. This strategy enables the model to dynamically adjust learner representations at different time intervals, allowing it to learn more accurate global behavioral patterns based on the characteristics of interactions and preference intensity across time. Through the gating mechanism, the model can gradually integrate the interaction information of learners from each time interval, ultimately learning the long-term interests and preferences exhibited by international Chinese learners throughout the entire interaction process. The fusion principle is as follows:

$$a_{u,s+1}^0 = hE_1 a_{u,s}^{M_F} + (1 - hE_1) a_{u,s}^0$$

$$hE_1 = \frac{\exp(Q_{C_1}^s \delta(Q_{E_1} a_{u,s}^{M_F}))}{\exp(Q_{C_1}^s \delta(Q_{E_1} a_{u,s}^{M_F})) + \exp(Q_{C_1}^s \delta(Q_{E_1} a_{u,s}^0))} \tag{10}$$

This framework, which integrates HGAM and gating strategies, enables the model to accurately understand the global preferences of international Chinese learners. Within each time interval, the HGAT helps capture learners' short-term interests and preferences, while the gating strategy ensures that the model can balance the influence of different moments when processing cross-time behaviors. This results in a global learner representation that not only reflects the behavioral characteristics of learners at a single moment but also reveals the evolutionary trends of their preferences throughout the entire interaction process.

3.3 Interaction behavior prediction

To effectively capture the interaction patterns and preference changes of international Chinese learners, we learn the representations of learners in each time interval and fuse them into a global dynamic interest and preference representation. Specifically, during each interaction prediction, we retrieve the most recently interacted learner representations $C_l^D = [g_u]$, which contain information related to the learner's interaction relationships. These interaction relationships, modeled jointly

through the HGAM and GCN, effectively reveal the dynamic interaction characteristics among learners. Additionally, we retrieve the latest time interval learner representations $w_l^F = [(a_u, s)]$ and cascade representations $o_l^F = [(p_l, s)]$ from the global preference learning module. These representations reflect learners' interest changes and their interaction history with other learners. The formulas are given as follows:

$$C_l^F = hE_2 w_l^F + (1 - hE_2) o_l^F$$

$$hE_2 = \frac{\exp(Q_{C_2}^S \delta(Q_{E_2} o_l^F))}{\exp(Q_{C_2}^S \delta(Q_{E_2} o_l^F)) + \exp(Q_{C_2}^S \delta(Q_{E_2} w_l^F))} \quad (11)$$

To integrate this information, we adopt a gating mechanism. The gating mechanism flexibly adjusts the weights between cascade representations and learner representations, allowing it to capture dynamic preference changes in the time sequence. Specifically, the gating mechanism learns short-term dynamic changes and long-term preference trends for each time interval, generating a more accurate and expressive learner representation e_l . This representation integrates learners' interaction relationships, interest preferences, and temporal dynamics, serving as the foundation for subsequent predictions. The formulas are as follows:

$$e_l = hE_3 C_l^F + (1 - hE_3) C_l^F$$

$$hE_3 = \frac{\exp(Q_{C_3}^S \delta(Q_{E_3} C_l^F))}{\exp(Q_{C_3}^S \delta(Q_{E_3} C_l^F)) + \exp(Q_{C_3}^S \delta(Q_{E_3} C_l^D))} \quad (12)$$

Through this approach, the model can not only capture the local interaction information of the learner at a specific moment but also understand the behavioral changes of the learner across the entire time series, thereby better predicting their interaction behaviors at future time points. After obtaining the fused international Chinese learner representations e_p , we construct a time series $E = \{e_1, e_2, \dots, e_L\}$, where each e_l represents the learner's representation at the l -th time interval. Next, we input this sequence into the mask multi-head attention mechanism to detect potential dynamic interactions. Let the mask matrix be represented by L , and when $u > k$, i.e., $L = -\infty$, the attention is closed when the time range is exceeded. Q_u^W, Q_u^I, Q_u^N, Q^P are learnable parameters, and $f_e = f/V$, where V is the number of heads in multi-head attention. The prediction formulas are:

$$ATT(W, J, N) = \text{softmax} \left(\frac{WJ^S}{\sqrt{f_j}} + L \right) N$$

$$y_u^f = AT(EQ_u^W, EQ_u^I, EQ_u^N) \quad (13)$$

$$T = [y_1; y_2; \dots; y_V] Q^P$$

The advantage of the mask multi-head attention mechanism in processing time series is that it can parallelly capture contextual information between different time intervals. Compared to traditional RNN or LSTM structures, it can more efficiently and accurately model long-term and short-term dependencies in time series. Through the multi-head attention mechanism, the model can automatically adjust the attention given to each time interval, thus identifying possible interaction effects over a larger range for prediction. This mechanism captures potential interaction effects

between time intervals step by step through multiple iterations. After obtaining the sequence T processed by the mask multi-head attention mechanism, we compute the probability of dynamic interaction through a two-layer fully connected neural network. The fully connected layers, through nonlinear activation functions, further enhance the model's expressive power. The final output is the probability distribution of the international Chinese learner interacting in the future time intervals. This prediction reflects the learner's possible interaction decisions at future moments based on past interaction behaviors and preference changes. Assume that the learnable parameters are represented by Q_4, Q_5, η_1, η_2 , then the formula is:

$$\hat{b} = Q_5 \text{ReLU}(Q_4 T^s + \eta_1) + \eta_2 \quad (14)$$

Let all the parameters to be learned be represented by φ . If the international Chinese learner participates in the cascade at the u -th step, then $b_{uk} = 1$, otherwise, $b_{uk} = 0$. The loss function used by the model is:

$$m(\varphi) = - \sum_{u=2}^{|Z|} \sum_{k=1}^{|I|} b_{uk} \log(\hat{b}_{uk}) \quad (15)$$

4 EXPERIMENTAL RESULTS AND ANALYSIS

From Tables 1 and 2, it can be seen that the model proposed in this paper outperforms traditional models on all datasets and evaluation metrics. Specifically, in terms of Hits@N metrics (N = 10, 50, 100), the proposed model consistently outperforms other models across all three datasets. For example, on the online Chinese course interaction text dataset, the proposed model scores 22.48%, 35.69%, and 45.69% at @10, @50, and @100, respectively, which is significantly higher than other models (e.g., the RNN-Attention model scores 18.75% at @10). A similar trend is observed on the Chinese learning app in-app message text dataset and the professional Chinese learning forum posts and replies dataset, especially in the @50 and @100 scores, where the proposed model's performance is stable and outstanding. In terms of MAP@N metrics, the proposed model also maintains an advantage across all datasets, especially on the Chinese learning app in-app message text dataset and the professional Chinese learning forum posts and replies dataset, where the MAP@50 and MAP@100 scores are more outstanding than other models, indicating the robustness and accuracy of the proposed model in handling large-scale data.

Table 1. Experimental results on different datasets (%) (hits@N scores for N = 10, 50, 100)

	Online Chinese Course Interaction Text Dataset			Chinese Learning App In-app Message Text Dataset			Professional Chinese Learning Forum Posts and Replies Dataset		
	@10	@50	@100	@10	@50	@100	@10	@50	@100
HAN	9.15	13.84	18.25	5.69	11.58	17.56	11.56	22.36	31.26
VAE	8.62	15.23	22.36	8.32	14.26	24.63	11.85	21.38	32.56
DBN	15.47	26.35	34.51	24.56	35.23	41.26	16.35	34.26	47.52
RNN-Attention	18.75	31.25	38.59	27.69	41.56	48.56	23.48	41.85	52.36
Bi-LSTM-CRF	17.62	31.84	38.54	32.51	44.89	51.25	25.69	41.36	51.36
GRU-Attention	22.36	34.25	41.23	32.58	48.62	57.02	27.51	46.89	54.89
The Proposed Model	22.48	35.69	45.69	33.26	52.36	62.39	28.36	48.52	57.36

Table 2. Experimental results on different datasets (%) (map@N scores for N = 10, 50, 100)

	Online Chinese Course Interaction Text Dataset			Chinese Learning App In-app Message Text Dataset			Professional Chinese Learning Forum Posts and Replies Dataset		
	@10	@50	@100	@10	@50	@100	@10	@50	@100
HAN	6.25	6.89	7.28	5.69	6.78	6.23	7.12	7.74	7.74
VAE	6.35	7.26	7.69	8.74	11.26	12.54	7.89	8.51	9.56
DBN	11.25	12.36	12.62	14.23	15.64	15.69	8.52	8.84	9.32
RNN-Attention	12.98	12.45	12.41	18.26	21.68	22.31	13.26	14.26	14.26
Bi-LSTM-CRF	11.26	12.32	12.23	21.23	22.36	22.58	14.56	15.20	15.28
GRU-Attention	11.85	11.52	11.56	21.03	22.15	22.69	16.89	17.56	15.62
The Proposed Model	11.96	12.36	13.26	22.56	23.15	24.31	17.63	18.36	18.56

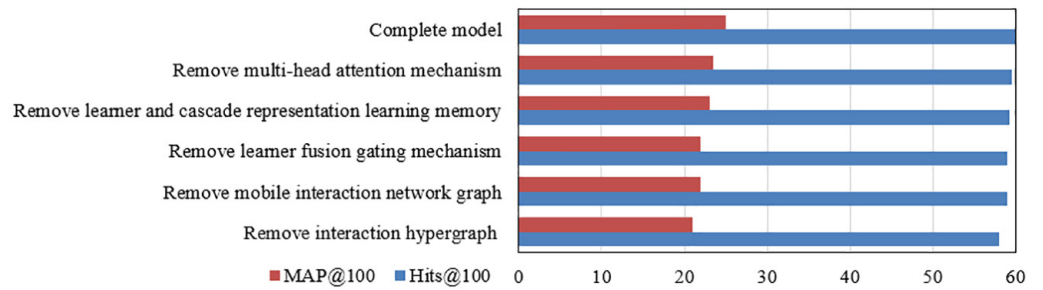


Fig. 5. Ablation experiment on the model

From the results in Figure 5, it is evident that each module has an impact on the final model performance. In the two metrics, Hits@100 and MAP@100, removing any key module leads to a decline in model performance. Specifically, after removing the HGAM, the model's score in Hits@100 drops to 58, and MAP@100 falls to 21. Removing the mobile interaction network graph results in a slight increase in Hits@100 to 59, but it still lags behind the complete model (60). When the learner fusion gating mechanism is removed, Hits@100 becomes 59.3 and MAP@100 is 23, indicating that the gating mechanism is crucial for the dynamic fusion of learner behaviors. Removing the multi-head attention mechanism slightly decreases the scores (59.5 and 23.5), but compared to the complete model's performance, it still shows the importance of the attention mechanism in capturing contextual information. These ablation experiment results suggest that the removal of any module affects the model's prediction ability to some extent, especially the removal of the HGAM, mobile interaction network graph, and gating mechanism, which leads to a significant performance drop.

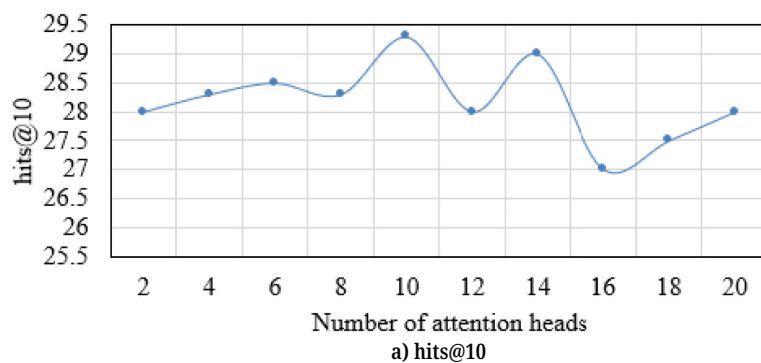


Fig. 6. (Continued)

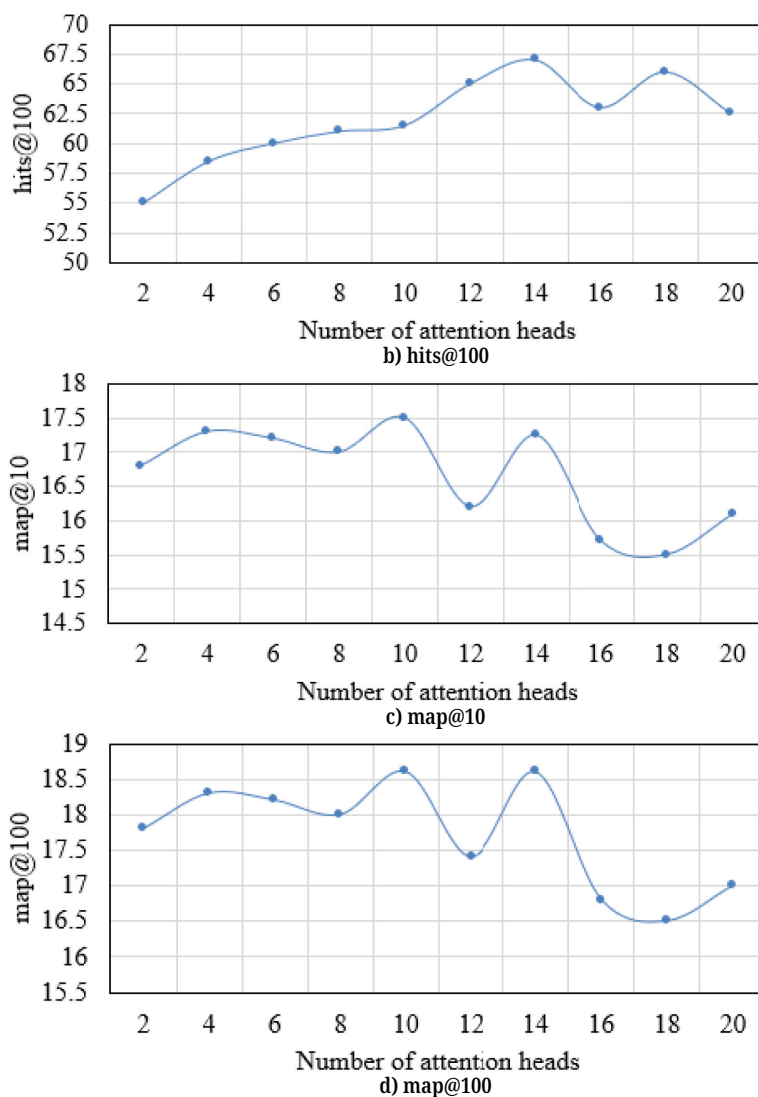


Fig. 6. Comparison of model performance metrics with different numbers of heads

From the experimental data in Figure 6, it can be seen that as the number of attention heads increases, the model’s performance fluctuates, but overall, the performance improves with more heads. In the metrics of Hits@10 and Hits@100, the best performance occurs when there are 12 or 14 heads, especially at Hits@100, where the highest score (67) is achieved with 14 heads, followed by 12 heads (65) and 10 heads (61.5). In MAP@10 and MAP@100, the performance improvement is relatively steady, with 12 and 14 heads performing relatively well. Specifically, MAP@100 reaches 18.6 when there are 14 heads, slightly higher than other head settings. Overall, increasing the number of attention heads improves the model’s performance to some extent, particularly in higher ranks (Hits@100 and MAP@100), as more attention heads help capture different levels of learner interactions and preference information.

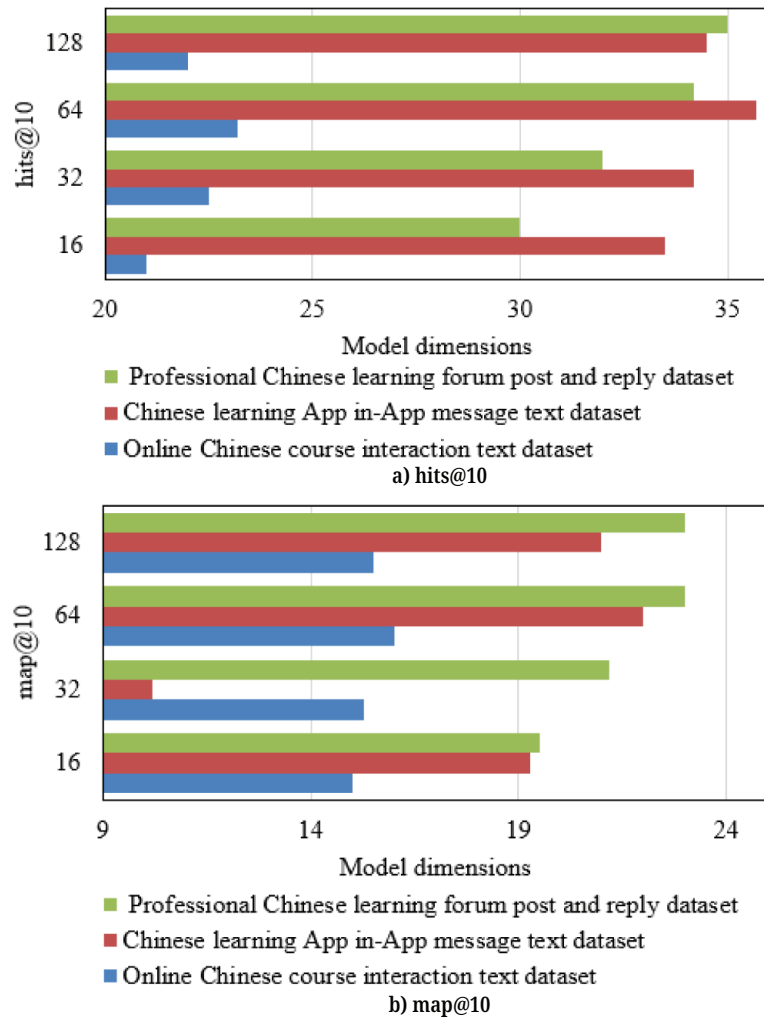


Fig. 7. Comparison of model performance metrics with different dimensions

From the experimental data in Figure 7, it can be seen that as the model dimension increases, the performance improves to some extent, but the performance difference varies greatly between different datasets. In the case of Hits@10, for the online Chinese course interaction text dataset, as the model dimension increases from 16 to 128, Hits@10 gradually improves from 21 to 23.2, indicating that higher dimensions help capture more interaction information. For the in-app message text dataset of a Chinese learning app, the increase in dimensions from 16 to 128 leads to a notable improvement, from 33.5 to 34.5, suggesting that the dataset can benefit from higher dimensions for more accurate learner behavior prediction. For the professional Chinese learning forum post and reply dataset, the best performance occurs with a dimension of 128, where Hits@10 reaches 35, showing a significant improvement compared to the lower dimension (16). For MAP@10, although the increase in dimension generally enhances performance in most datasets, the effect is not as significant as in Hits@10. For the in-app message text dataset and the professional Chinese learning forum post and reply dataset, when the dimension increases to 64 or 128, MAP@10 reaches 22 and 23 respectively, showing an improvement over the 16-dimension setting, but the change is not as noticeable as for Hits@10.

These results show that increasing the model's dimension has a positive effect on improving the accuracy of predicting the behavior of international Chinese learners, especially when dealing with complex interaction data. Higher dimensions allow

for better capturing of learner interaction relationships and behavior characteristics. Especially in the in-app message dataset of a Chinese learning APP and the professional Chinese learning forum post and reply dataset, increasing the dimension significantly improved the model's performance. This also reflects the complexity and diversity of interactive behaviors in the Chinese learning scenario, requiring models to handle more levels of information. For personalized learning prediction of international Chinese learners, as the diversity of learner behaviors and preferences increases, mobile interaction technology, through higher-dimensional feature representation, can more accurately capture these changes, providing stronger data support for personalized teaching.

5 CONCLUSION

This study proposed a mobile interactive learning prediction model for international Chinese learners by combining the HGAM with graph convolution networks. Through experimental validation on different datasets, the study shows that this model can effectively improve the accuracy of Chinese learner behavior prediction, particularly in complex learning scenarios. By capturing the interaction relationships and global preferences between learners, the model enables personalized and intelligent learning recommendations. The research not only optimized the algorithm design, allowing the HGAM to accurately model learner interaction relationships, but also demonstrated the potential of this technology in practical applications, such as promoting personalized teaching in Chinese education through enhanced understanding of learner interaction data. Additionally, the experimental results proved the value of AI technology in the field of Chinese learning, particularly in improving learner outcomes and providing personalized teaching paths.

However, despite the excellent predictive accuracy of the proposed model, there are still certain limitations. First, the experimental datasets are relatively limited. While they cover different Chinese learning interaction scenarios, a more diverse and comprehensive dataset would help further validate the model's generalizability and robustness. Second, the model optimization and parameter selection can be further refined, particularly regarding the combination of the HGAM and graph convolution networks. There are still many details to explore, such as how to more effectively handle the nonlinear relationships of learner behaviors and how to balance computational efficiency and predictive accuracy. These are issues that future research should focus on. Furthermore, as the group of Chinese learners continues to evolve, future research can explore how to apply the model to more diverse learning scenarios, such as multilingual learning and cross-cultural education, and combine it with real-time feedback mechanisms to further enhance the effectiveness of intelligent learning systems. Ultimately, this study provides a technical framework and theoretical foundation for future personalized learning in Chinese education based on AI, with significant theoretical and practical application value.

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