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PAPER

The Impact of Mobile Interactive Technologies on Promoting Students' Innovative Capabilities in Higher Education

Guoyun Chen(✉)

Zhengzhou Professional Technical Institute of Electronic & Information, Zhengzhou, China

cguoyun2023@163.com

ABSTRACT

This paper aims to explore the impact of mobile interactive technologies on fostering the development of students' innovative capabilities in higher education and proposes a solution to the sequential recommendation problem. Initially, we define the importance of students' innovative capabilities and identify the potential applications of mobile interactive technologies in this context. We analyze existing research and identify limitations in meeting individualized student needs, mobile interactive social relationships, and contextual information. To address this research gap, this paper presents a specific definition of the sequential recommendation problem that aims at enhancing the development of students' innovative capabilities and constructs a sequential recommendation model that integrates contextual information and mobile interactive social relationships. Composed of an embedding representation layer, a spatial-temporal hierarchical pooling (SHP) layer, and a fusion prediction layer, this model is designed to better capture students' personalized learning preferences and social influences, offering precise learning resource recommendations to promote the development of their innovative capabilities.

KEYWORDS

higher education, mobile interactive technologies, students' innovative capabilities, sequential recommendation, personalized learning, mobile interactive social relationships, contextual information

1 INTRODUCTION

As mobile Internet technologies rapidly develop, the field of higher education is increasingly exploring and applying mobile interactive technologies to foster the development of students' innovative capabilities [1–4]. Students' innovative capabilities are not only one of the core objectives of higher education but also an essential skill for dealing with increasingly complex social environments and rapidly changing

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workplace demands [5, 6]. Against this backdrop, this paper aims to discuss the role of mobile interactive technologies in enhancing students' innovative capabilities and proposes corresponding solutions to the sequential recommendation problem in hopes of providing theoretical support and practical guidance for the reform and development of higher education.

The application of mobile interactive technologies in higher education has achieved certain results, but their impact on the development of students' innovative capabilities still warrants further study [7–10]. Students' innovative capabilities are influenced not only by individual learning interests and abilities but also by the selection of learning resources and the educational environment. Therefore, exploring how to use mobile interactive technologies to provide personalized learning resource recommendations and how to integrate mobile interactive social relationships and contextual information to stimulate students' innovative potential is of great significance for improving the quality and effectiveness of higher education [4, 11].

Although some studies have explored the application of mobile interactive technologies in higher education, existing methods still have some limitations. Firstly, existing learning resource recommendation models often overlook the impact of individual differences among students and mobile interactive social relationships, resulting in recommendations that lack personalization and specificity [12–14]. Secondly, existing methods often consider only a single type of contextual information when addressing the sequential recommendation problem, lacking a deep understanding and exploration of students' learning behaviors [15–17]. Therefore, it is necessary to propose a new sequential recommendation model that fully considers students' personalized needs and mobile interactive social relationships, as well as rich contextual information.

This paper is divided into two main parts. Firstly, we provide a specific definition of the sequential recommendation problem aimed at enhancing the development of students' innovative capabilities, clarifying the research objectives and scope. Secondly, we construct a sequential recommendation model that integrates contextual information and mobile interactive social relationships, which includes an embedding representation layer, an SHP layer, and a fusion prediction layer. Through this model, we can better capture students' personalized learning preferences and social influences, providing precise recommendations for learning resources and thereby promoting the development of their innovative capabilities. The research findings of this paper not only provide theoretical support for the reform and development of higher education but also offer practical references for the application and innovation of educational technology.

2 APPLICATION OF MOBILE INTERACTIVE TECHNOLOGIES TO ENHANCE STUDENTS' INNOVATIVE CAPABILITY DEVELOPMENT

In higher education, the application scenarios of mobile interactive technologies involve course selection, learning resource recommendations, and academic literature retrieval. In these scenarios, students' behaviors are often interconnected, with current preferences and behaviors influenced by previous ones. The sequential recommendation system views students' historical learning behaviors as a sequence, where learning resources, activities, learning paths, and partners are arranged in chronological order.

Based on this sequence, the sequential recommendation system can analyze students' past learning behaviors, capturing learning preferences and transition trends at different times. By modeling the continuous items in the sequence, the system can discover the sequential transition relationships in the learning process, thereby inferring the next likely learning need or behavior.

For innovative learning resources and activities, the sequential recommendation system can predict innovative topics or areas of interest for the student based on their historical learning preferences and behaviors and recommend relevant learning resources and activities. For example, if a student frequently accessed courses and articles related to artificial intelligence, the system might infer the student's interest in the field of artificial intelligence and recommend related innovative projects or seminars.

For innovative learning paths and strategies, the sequential recommendation system can tailor innovative learning paths and strategies for students based on their previous learning history and performance data. The system can analyze students' performances at different learning stages, predict learning paths and methods that suit their personalized needs, and provide corresponding advice and guidance.

For innovative-related collaborative partners or team collaboration opportunities, the sequential recommendation system can recommend suitable partners or team collaboration opportunities by analyzing students' learning social networks and collaboration histories. The system can discover students' preferences and performances in past collaborations, predict partners or teams that share similar goals, and recommend appropriate collaboration opportunities.

Existing sequential recommendation algorithms applied to scenarios for enhancing students' innovative capabilities face the following three challenges:

1. Limited to modeling a single student's sequence: Traditional sequential recommendation algorithms typically focus only on an individual student's learning sequence, ignoring the impact of co-occurring items in other students' sequences. In higher education, there is rich interaction and collaboration among students, and their learning behaviors are often influenced by each other. Therefore, modeling only the items within a single student's sequence ignores the interactions and collaborations among students, thus limiting the comprehensive promotion of students' innovative capabilities by the recommendation system.
2. Lack of modeling the influence of multiple items: Existing sequential recommendation algorithms mainly focus on pairwise relationships between items but overlook the combined impact of multiple items on the current item. In higher education, students' learning processes often involve multiple disciplines and knowledge points, where complex relationships may exist between different knowledge points. Considering only single items may lead to ambiguities in the prediction results of the recommendation algorithms, failing to fully explore the connections and combined impacts between knowledge points, thus limiting the depth of support the recommendation system can provide for the development of students' innovative capabilities.
3. Ignoring the impact of mobile interactive social relationships: Existing sequential recommendation algorithms often overlook the impact of mobile, interactive social relationships among students on learning behaviors. However, in higher education, mobile, interactive social relationships among students are very important, as they often influence and promote each other through

communication and collaboration. Therefore, recommendation algorithms need to consider the impact of mobile interactive social relationships on students' learning behaviors to better understand their preferences and needs, thereby providing more personalized and effective recommendation support to promote the comprehensive development of their innovative capabilities.

Thus, sequential recommendation algorithms aimed at enhancing the development of students' innovative capabilities need to address the challenges of focusing only on individual student sequences, lacking modeling of the impact of multiple items, and ignoring mobile, interactive social relationships to better support the application scenarios of mobile, interactive technologies in higher education and promote the development of students' innovative capabilities.

3 DEFINITION OF SEQUENTIAL RECOMMENDATION PROBLEM FOR ENHANCING STUDENTS' INNOVATIVE CAPABILITY DEVELOPMENT

In response to the issues analyzed in the previous section, this paper proposes a sequential recommendation model that integrates contextual information with mobile interactive social relationships and is applied to enhance students' innovative capability development. The model constructs a hypergraph of session data. That is, students' learning behavior data is transformed into session data, each session representing a continuous sequence of learning activities. These session data are then constructed into a hypergraph structure, where nodes represent the items students interact with in sessions and hyperedges represent the associations between items. When constructing the hypergraph, the contextual information of items within sessions and the associations between items across sessions are considered to comprehensively capture students' learning behaviors. Information on students' mobile interactive social relationships is introduced into the hypergraph, mapping the mobile interactive social relationships between users as the weight or attributes of hyperedges. Thus, the recommendation system can take into account the social influences among students, such as how a student's friends might influence their learning behaviors, thereby more accurately understanding students' learning preferences and needs.

The model divides students' preferences into long-term, short-term, and current preferences. Long-term preferences reflect the student's stable, long-standing interests and preferences; short-term preferences reflect the student's temporary interests during the current period; current preferences pertain to the most recent item the student interacted with. By considering these three types of preferences, a more comprehensive understanding of students' learning status and needs can be achieved. Based on the constructed hypergraph of session data and integrated mobile interactive social relationship information, the recommendation system can use technologies such as deep neural networks to make sequential recommendations for students' learning behaviors. The system can analyze students' learning histories, contextual information, and mobile interactive social relationships, predict the next learning need or behavior, and recommend personalized innovative learning resources, learning paths, and collaborative opportunities, thereby promoting the development of their innovative capabilities. Figures 1 and 2 illustrate the sequential contextual information and mobile interactive social relationships, respectively.

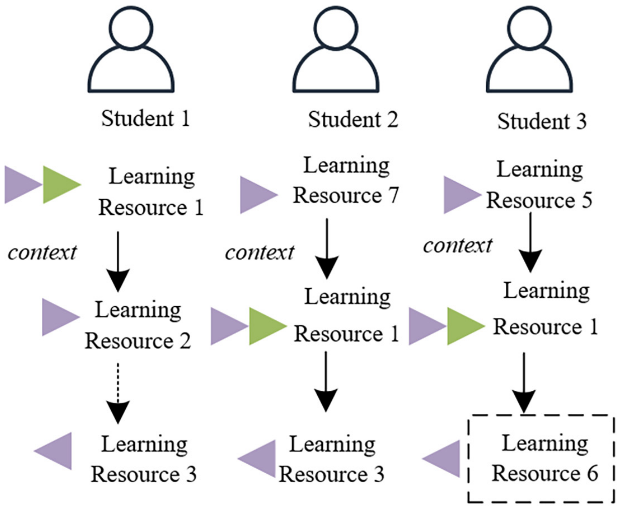

Fig. 1. Schematic diagram of sequential context information

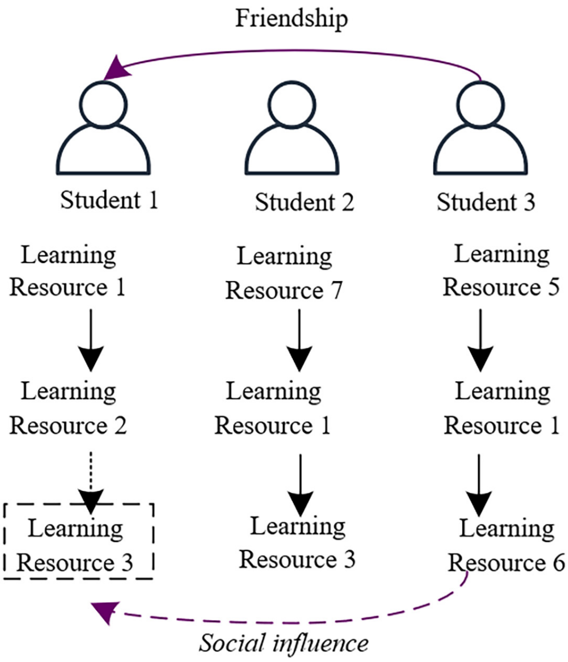

Fig. 2. Schematic diagram of mobile interactive social relationships

The sequential recommendation problems for enhancing students' innovative capability development are defined as follows:

1. Set of students and learning resources: The set of students $I = \{i_1, i_2, \ldots, i_l\}$ represents all students participating in learning activities, where L is the number of students. The set of learning resources $N = \{n_1, n_2, \ldots, n_V\}$ represents the learning resources or activities that students can access, with V being the number of resources or activities.
2. Interaction matrix between students and learning resources: $B = (b_{in})_{i\in I, n\in N}$ represents the interaction matrix between student i and learning resource n. If student i has had implicit interaction with resource n, b_{in} is set to 1, otherwise, it is 0.
3. Social (friendship) relationships among students: Matrix $D = (d_{il})_{i\in I, l\in I}$ represents the mobile interactive social relationships among students. If student i

has interacted with student l (e.g., joint participation in projects, collaborative research), then d_{il} is 1, otherwise, it is 0. The set of friends of student i is represented as $D_i = \{l \mid d_{il} = 1, \forall l \in I\}$.

4. Long-term and short-term interaction sequences of students: Long-term interaction sequence $T^i = \{t_1^i, t_2^i, \ldots, t_{ti}^i\}$ represents the long-term preference sequence of student i, arranged in the order of interaction, with length $|T^i|$. Short-term interaction sequence $T^i = \{t_1^i, t_2^i, \ldots, t_v^i\}$: represents the sequence of the last j learning resources that student i has interacted with.
5. Construction of the hypergraph: The hypergraph $GH_i = (N_i, R_i)$ captures the set of learning resources $N_i \subseteq N$ that student i and their friends D_i have interacted with, and the set of hyperedges $R_i = \{T_j^g \mid g \in \{i\} \cup D_i\}$formed by the short-term interaction sequences of student i and their friends D_i.
6. Definition of the association matrix: The association matrix $F_i = (f_{uk}^i)_{u \in N, k \in Ri}$ where f_{uk}^i indicates that the learning resource node n_u appears in the hyperedge r_k.

Given T^i, D, GH_i, the probability distribution estimation function for $\forall n \in N$ is denoted by $d(\cdot)$. Given T^i, D, GH_i, the task of the constructed model is to recommend the next t_{v+1}^i based on i's historical behavior, as defined by Equation (1):

$$\hat{b} = d\left(n \middle| T^i, D, GH_i, \forall u \in N\right) \tag{1}$$

The model ultimately selects the learning resource with the highest probability as the candidate recommendation t_{v+1}^i.

4 CONSTRUCTION OF THE SEQUENTIAL RECOMMENDATION MODEL FOR ENHANCING STUDENTS' INNOVATIVE CAPABILITY DEVELOPMENT

Combining the application scenarios of mobile interactive technologies in higher education and the goal of fostering students' innovative capabilities, this paper outlines the construction of a SHRec model for sequential recommendation aimed at enhancing students' innovative capabilities. The model includes an embedding representation layer, an SHP layer, and a fusion prediction layer. The embedding representation layer randomly initializes each learning resource in the target student's interaction sequence as a vector representation. Using a self-attention module, the model represents the target student's long-term preferences to capture the associations and importance of the student's long-term learning behaviors. The SHP layer considers the student's short-term preferences as contextual information, including the learning resources recently interacted with by the student. Using the contextual learning resources of the target student and their friends, a hypergraph is constructed, associating the learning behaviors of the student and their friends (see Figure 3). The hyperedges in the hypergraph are embedded, and taking into account the impact of students' mobile interactive social relationships on learning behaviors, these relationships are used to propagate the hyperedge representations, obtaining updated representations of the hyperedges. These updated representations of the hyperedges are then used to reverse update the representations of each learning resource within the hyperedge, thus obtaining new representations of the learning resources. The fusion prediction layer merges the representations of the student's long-term preferences, the reverse updated learning resource representations, and the hyperedge representations. Based on these merged representations, the model predicts the next learning resource the target student may interact with, providing personalized learning resource recommendations to foster the development of the student's innovative capabilities.

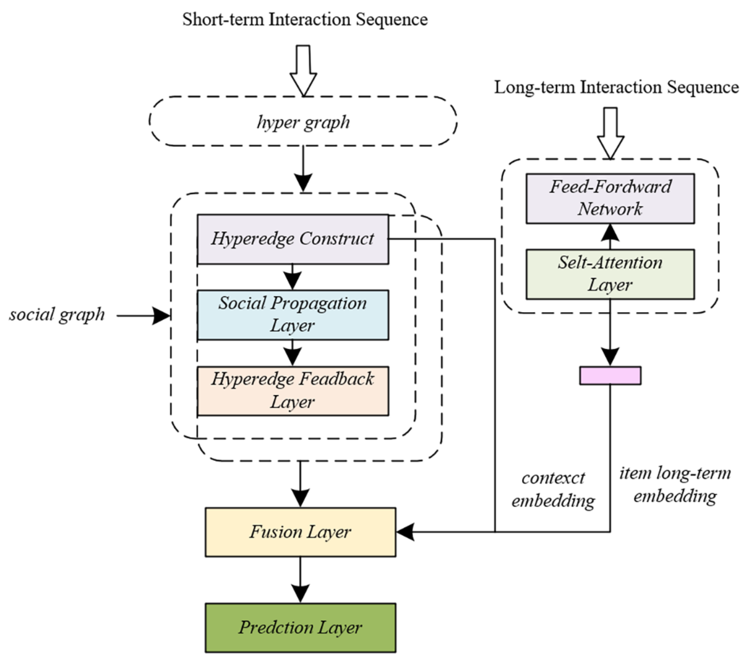

Fig. 3. Overall framework of the sequential recommendation model for enhancing students' innovative capability development

4.1 Embedding representation layer

The purpose of the embedding representation layer is to embed the representations of learning resources from the interaction sequence into a low-dimensional, dense space. Define learnable student embedding lookup table I and learning resource embedding lookup table N, which respectively represent the embedding matrices for students and learning resources. Each row in these lookup tables corresponds to an embedding representation of a student or learning resource. The dimension of the student embedding lookup table I is $L \times f_i$, where L is the number of students and f_i is the dimension of the student embeddings. The dimension of the learning resource embedding lookup table N is $V \times f_n$, where V is the number of learning resources and f_n is the dimension of the learning resource embeddings. Given the long-term interaction sequence $T^i = \{t_1^i, t_2^i, \ldots, t_v^i\}$ and the short-term interaction sequence $T_j^i = \{t_{v-m+1}^i, t_{v-j+2}^i, \ldots, t_v^i\}$, the initial embedding representation of t_u^i is denoted by $n_{v,u}$, and its embedding representation is:

$$R_i^M = \begin{bmatrix} n_{i,1} \\ n_{i,2} \\ \vdots \\ n_{i,v} \end{bmatrix} \in \Re^{v \times f_n}, R_i^T = \begin{bmatrix} n_{i,v-j+1} \\ n_{i,v-j+2} \\ \vdots \\ n_{i,v} \end{bmatrix} \in \Re^{j \times f_n} \tag{2}$$

For a given student i, with their long-term interaction sequence $T^i = \{t_1^i, t_2^i, \ldots, t_v^i\}$ and short-term interaction sequence $T_j^i = \{t_{v-m+1}^i, t_{v-j+2}^i, \ldots, t_v^i\}$, where v is the length of the sequence and j is the length of the short-term interaction sequence. First, the learning resources in the long-term interaction sequence T^i are retrieved through the learning resource embedding lookup table N to obtain the initial embedding representation R_i^M. Further, R_i^M is fed into a self-attention module to capture the sequential dependencies among learning resources. The self-attention mechanism assigns different importance weights to different learning resources, allowing the model to better understand the learning behavior patterns of students. Finally, the representation R_i^M processed by the self-attention module is fed into a feed-forward layer, resulting in the long-term preference representation $\tilde{R}_i^M$ for student i, which contains an abstract representation of important features and sequential relationships of learning resources in the long-term interaction sequence. The branch weight matrices are represented by Q^W, Q^G, Q^N, Q, $Q^{\sim}$, and the bias vectors are represented by y, $y^{\sim}$, with the activation function represented by $\delta(\cdot)$. The formulas are as follows:

$$\hat{R}_i^M = SM\left(\frac{R_i^M Q^W (R_i^M Q^G)^S}{\sqrt{f_n}}\right)\cdot(R_i^M Q^N) \tag{3}$$

$$\tilde{R}_i^M = \delta(\hat{R}_i^M Q + y)\cdot\tilde{Q} + \tilde{y} \tag{4}$$

4.2 SHP layer

The principle of the SHP layer is to utilize a hypergraph structure to model the mobile interactive social relationships among students and the associations between learning resources, updating the representations of learning resources through a multi-layer message passing mechanism to better capture the students' personalized learning preferences and social influences. For each target student i, a hypergraph $GH_i = (N_i, R_i)$ is constructed, where the node n represents a learning resource, and hyperedges are formed by the short-term preferences of the target student i and its friends. This hypergraph structure effectively captures the associations between students and between students and learning resources.

The initial embedding representations $\{n_1^{(0)}, n_2^{(0)}, \ldots, n_n^{(0)}\}$ of each hypergraph node $\{n_1, n_2, \ldots, n_o\}$ are used as the initial propagation of messages. Through the message-passing mechanism of the SHP layer, the embedding representation of node n_u is propagated to hyperedge r_k, generating a message vector $l_{u\to k}^{(1)}$. Assuming the embedding representation of hyperedge r_k is denoted by i_k, and the similarity function is represented by $SIM(\cdot)$, it is expressed as:

$$l_{u\to k}^{(1)} = \beta_{ku} Q_1^{(1)} n_u \tag{5}$$

$$\beta_{ku} = \frac{SIM(\hat{Q}_1^{(1)} n_u, i_k)}{\sum_{\{g|f_{gk}^i=1\}} SIM(\hat{Q}_1^{(1)} n_u, i_k)} \tag{6}$$

Using the message aggregation operation, the message vectors of all hyperedges r_k associated with node n_u are aggregated to form the embedding representation of hyperedge r_k, $r_k^{(1)}$. Assuming the aggregation function is represented by $\Gamma(\cdot)$, the expression is:

$$r_u^{(1)} = \Gamma\left(\left\{l_{u\to k}^{(1)} \middle| f_{uk}^i = 1\right\}\right) \tag{7}$$

Utilizing the attention mechanism to perform weighted aggregation on the set of hyperedges $G_u = \{r_k \mid f_{uk}^i = 1\}$ where node n_u is located, considering the influence of friends. The hyperedge representation considering the influence of friends is updated along with the embedding representation of node n_u, resulting in a new embedding representation for node n_u. Assuming the embedding representation of hyperedge r_k influenced by friends' preferences is denoted by $\hat{r}_k$, it is calculated as:

$$l_{k\to u}^{(1)} = \alpha_{ku} Q_2^{(1)} r_k \tag{8}$$

$$\alpha_{ku} = \frac{SIM(\hat{Q}_2^{(1)}\hat{r}_k, Q_3^{(1)} n_u)}{\sum_{g\in G_u} SIM\left(\hat{Q}_2^{(1)}\hat{r}_k, Q_3^{(1)} n_u\right)} \tag{9}$$

$$n_u^{(1)} = \Gamma\left(\left\{l_{k\to u}^{(1)} \middle| k \in G_u\right\}\right) \tag{10}$$

The calculation of $\hat{r}_k$ is as follows:

$$\hat{r}_k = \omega r_k + (1-\omega)\sum_{i\in D_k} \eta_{ki} r_i \tag{11}$$

$$\eta_{ki} = \frac{SIM(Q_4^{(1)} r_i, Q_5^{(1)} e_k)}{\sum_{g\in Dk} SIM\left(Q_4^{(1)} r_i, Q_5^{(1)} e_k\right)} \tag{12}$$

Finally, by stacking multiple SHP layers to model multi-hop high-order messages passing in the hypergraph, the output from one layer serves as the input to the next layer until the predetermined number of layers M is reached. This approach better captures the complex associations between students' mobile interactive social relationships and learning resources, enhancing the model's expressive capability and recommendation effectiveness. Assuming the m-th layer's node and hyperedge embedding representation matrices are represented by $N_i^{(m)}$ and $R_i^{(m)}$ respectively, then there is:

$$N_i^{(m)}, R_i^{(m)} = SHP(N_i^{(m-1)}, R_i^{(m-1)}) \tag{13}$$

4.3 Fusion prediction layer

The principle of the fusion prediction layer is to combine the long-term, short-term, and current preference representations of a student, then calculate the preference scores for all learning resources and derive the final preference scores using the *Softmax* function. Initially, the long-term and short-term preference representations of the target student i are obtained using the embedding representation layer and the SHP layer. These representations include the student's long-term and short-term preferences, as well as the associative information between learning resources. Furthermore, the representation of the learning resource $n_{v,i}^{(M)}$ most recently interacted with by student i is selected as the current preference representation. This representation reflects the student's current learning interests and preferences. Assuming the fusion function is denoted by $\phi(\cdot)$, by combining these three types of preferences, the final representation of i's preferences, o_i, can be obtained:

$$o_i = \varphi(\tilde{R}_i^M, r_i^{(M)}, n_{i,v}^{(M)}) \tag{14}$$

For each learning resource n, the preference representation o_i and the learning resource representation n are multiplied to compute the preference score of student i for learning resource n:

$$e_{in} = O_i^S \cdot n \tag{15}$$

The preference scores for all learning resources are processed through the *Softmax* function to obtain the final preference scores $\hat{e}_i = SM([e_{i1}, e_{i2}, \ldots, e_{iN}])$ for student i. This step transforms the preference scores into a probability distribution, indicating the student's relative preference levels for different learning resources.

During the training process, a binary cross-entropy loss function is used to measure the difference between the predicted preference scores and the actual preference scores. Here, the actual preference score e_{is} represents the preference score of student i for the learning resource t_s^i with which they have interacted, while the negative sample set Ψ represents the set of other learning resources with which the student has not interacted. The model parameters ϕ are updated by minimizing the loss function, and model complexity can be controlled through the regularization term η to prevent overfitting.

$$\sum_{i} \sum_{s=1}^{v} \sum_{j \in \Psi} -\left[\log\left(e_{is}\right) + \log\left(1 - e_{is}\right)\right] + \eta \left\|\varphi\right\|^2 \tag{16}$$

5 EXPERIMENTAL RESULTS AND ANALYSIS

In the ablation study, the method utilizing hypergraphs showed approximately 2% and 1% improvements in HR@10 and NDCG@10, respectively, compared to the method without hypergraphs (refer to Table 1), indicating that the hypergraphs positively contributed to model performance. On the test set, our method showed improvements of about 2.3% and 0.7% in HR@10 and NDCG@10, respectively, compared to the baseline method, further validating the model's effectiveness and generalization capability on real datasets. From the analysis of the experimental results, it can be concluded that the model, utilizing components such as the embedding representation layer, SHP layer, and fusion prediction layer, can fully capture students' personalized learning preferences and social influences, thereby providing more accurate learning resource recommendations. Our method achieved significant improvements across multiple evaluation metrics compared to the baseline method, demonstrating the model's effectiveness and practicality.

Table 1. Ablation study results (HR represents HR@10, NDCG represents NDCG@10)

	Training Set		Test Set	
	HR	NDCG	HR	NDCG
Our Method with Hypergraph	0.2354	0.1568	0.4578	0.3215
Our Method	0.2347	0.1695	0.4621	0.3169
Our Method	0.2451	0.1654	0.4789	0.3158

The hyperparameter experiment results show that when the number of friends varies between 10 and 30 (see Figure 4), there is no clear regular pattern in the model's performance on the HR@10 metric, presenting some variability. Specifically, when the number of friends is 25, HR@10 reaches the highest value of 0.258, while at other numbers, the HR@10 values fluctuate between 0.247 and 0.255. This indicates that in this experimental setup, changes in the number of friends do not have a very significant impact on model performance, and the model demonstrates relatively stable recommendation capabilities across different numbers of friends. The experimental results suggest that the sequential recommendation model constructed in this study is somewhat robust to changes in the number of friends, further validating the model's effectiveness. Although the number of friends varies within a certain range, the model's performance on the HR@10 metric is not significantly affected, maintaining a high recommendation accuracy.

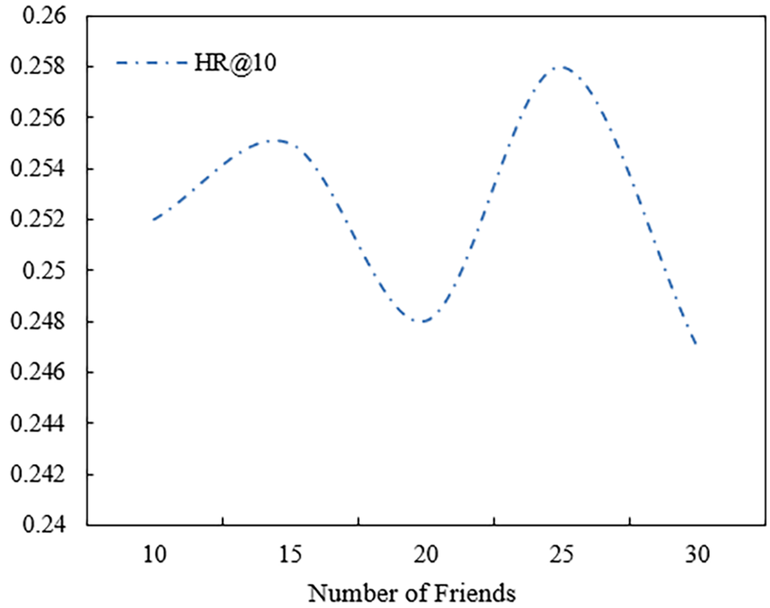

Fig. 4. Hyperparameter experiment results – number of friends (evaluation metric: HR@10)

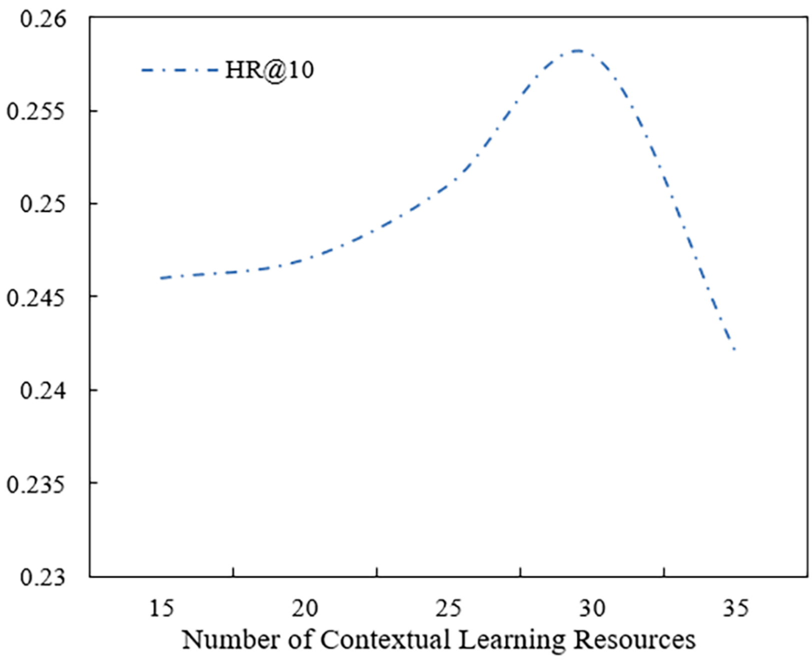

Fig. 5. Hyperparameter experiment results – number of contextual learning resources (evaluation metric: HR@10)

When the number of contextual learning resources changes from 15 to 35, the model's performance on the HR@10 metric exhibits certain fluctuations (see Figure 5). Specifically, when the number of contextual learning resources is 30, the model's HR@10 reaches its highest value of 0.258, while at other amounts, the HR@10 values fluctuate between 0.242 and 0.251. This indicates that in this experimental setup, the number of contextual learning resources has a fluctuating impact on model performance, and changes within a certain range noticeably affect the model's performance. It can be seen that the sequential recommendation model constructed in this study is somewhat sensitive to changes in the number of contextual learning resources. Despite the variation in the number of contextual learning resources within a certain range, the model's performance on the HR@10 metric is not monotonically increasing or decreasing but rather fluctuates within a certain range. Particularly when the number of contextual learning resources is 30, the model performs optimally, further validating the model's effectiveness.

Table 2. Impact of 75% training set on NDCG@10

75% Training Set	*HMM*	*RNN*	*NMF*	*LFM*	*DQN*	Our Method
Behavioral Dataset	0.1258	0.1784	0.1456	0.1895	0.2147	0.2214*
Academic Dataset	0.2564	0.2896	0.2689	0.3326	0.3269	0.3789*
Innovation Activity Dataset	0.1326	0.1785	0.1236	0.1658	0.1895	0.2258*
Background Dataset	0.5398	0.5896	0.5698	0.5794	0.6236	0.6789*

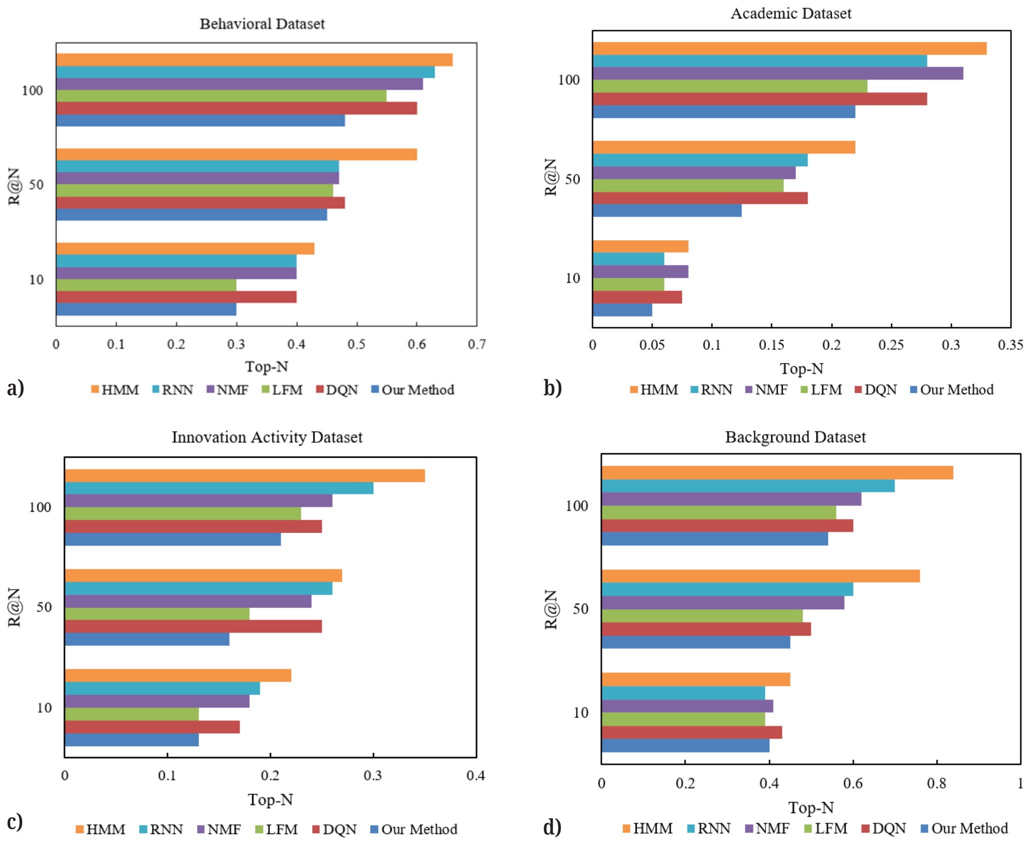

Fig. 6. The impact of changing the number of top N recommendations on R@N

According to the data in Table 2, the impact of different training sets on NDCG@10 can be observed. Across various types of datasets, our method achieved the best performance on the NDCG@10 metric, with values of 0.2214 (behavioral dataset), 0.3789 (academic dataset), 0.2258 (innovation activity dataset), and 0.6789 (background dataset). In comparison, other baseline models showed varying performances on their respective datasets, but none could comprehensively surpass the performance level of our method. It is evident that the sequential recommendation model constructed in this study performs excellently across different types of datasets, especially achieving the best NDCG@10 score on the background dataset. This indicates that the model can fully utilize the information in various types of datasets to more accurately capture students' personalized learning preferences and social influences.

Based on the data from the four graphs mentioned (see Figure 6), we observe how changing the number of top N recommendations affects the R@N metric across different models on various datasets. Overall, our method shows relatively stable and competitive recommendation performance across all datasets. Particularly on the innovation activity dataset and background dataset, our method achieved high scores across various R@N values, indicating good adaptability to different types of recommendation tasks. The analysis of experimental results demonstrates that the sequential recommendation model constructed in this study delivers good recommendation performance across different datasets for varying numbers of recommendations, further validating its effectiveness. Although other models might perform better in certain datasets and specific recommendation counts, considering all datasets and various numbers of recommendations, our method remains a reliable choice. Therefore, this model can flexibly adapt to different recommendation tasks, providing personalized learning resource recommendations to students, thereby fostering their development of innovative capabilities.

6 CONCLUSION

This paper addressed the sequential recommendation problem for enhancing students' innovative capability development. By clearly defining research objectives and scope, a sequential recommendation model that integrates contextual information and mobile interactive social relationships was constructed. This model includes an embedding representation layer, an SHP layer, and a fusion prediction layer designed to better capture students' personalized learning preferences and social influences, providing precise learning resource recommendations to promote their innovative capabilities.

Experimental results demonstrated the performance of the proposed sequential recommendation model under different experimental setups. Ablation study results and hyperparameter experiment results show significant improvements in evaluation metrics such as HR@10 and NDCG@10 compared to baseline methods, proving the model's effectiveness and practicality. Additionally, hyperparameter experiment results concerning the number of friends and contextual learning resources also verified the model's robustness and generalization ability. Moreover, analyses of the impact of training set size and recommendation number demonstrated the model's adaptability across different datasets and recommendation scenarios.

Considering the research content and experimental results, the proposed sequential recommendation model holds significant research value. However, there are some limitations, such as the scale and diversity of the experimental datasets, which might affect the model's generalizability. Future research directions could include further optimizing the model's algorithms and structure to enhance its applicability in broader scenarios, exploring more experimental setups, and evaluating metrics to comprehensively assess the model's performance. Additionally, integrating more disciplinary knowledge and technological methods to deeply explore students' personalized learning needs could make a greater contribution to the intelligent development of the educational field.

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8 AUTHOR

Guoyun Chen graduated from Renmin University of China in 2008 with a Master's degree. He is mainly engaged in research on Chinese language and literature. He is a senior engineer, and currently the President of Zhengzhou Professional Technical Institute of Electronics & Information, Zhengzhou 451450, China (E-mail: cguoyun2023@163.com; ORCID: https://orcid.org/0009-0001-8660-0060).