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RESEARCH ARTICLE

A Unified Learning Resource Recommendation Method Integrating Multidimensional Graph Information

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Abstract Personalized learning resource recommendation aims to provide learners with appropriate learning resources to alleviate information overload caused by the explosive growth of data on online learning platforms. Current research predominantly utilizes student interaction data to enhance the quality of recommendations. However, this approach neglects the intricate dependency networks among learning resources, which directly influence the effectiveness of knowledge acquisition pathways, and lacks the capacity to model individual learning abilities and objectives. To address these limitations, this study introduces a unified learning resource recommendation method (ULRRM), which integrates multidimensional graph information and employs conceptual graphs as an intermediary framework to unify resource representations across varying levels of granularity. Specifically, a resource dependency graph is established to guide resource-dependent learning through conceptual dependency relationships, thereby encoding the topological constraints of resources. Then, a local–global dual view is constructed using session history to capture both short-term behavioral patterns and the evolution of long-term interests, thereby enabling the recommendation of learning resource sequences that incorporate multidimensional graph information. Extensive experiments conducted on real datasets demonstrate that the proposed ULRRM method surpasses baseline approaches across several widely recognized evaluation metrics.

Keywords online education, learning resource recommendation, representation learning, resource dependency learning, sequential recommendation

1 Introduction

Artificial intelligence (AI)-enabled online learning platforms provide a large number of easily accessible resources and intelligent services (Bobko et al., 2024; Wang et al., 2022b), making online learning a widely adopted mode of teaching in many countries (Chang & Dao, 2026). However, statistics show that the overall completion rate for learning on online learning platforms ranges from 3% to 10% (Rahimi & Ghorbani, 2025), and this low completion rate is partly attributed to information overload caused by the large number of online resources, which fail to accurately match students' learning needs. Personalized learning resource recommendation is a promising solution to this problem and has attracted attention in both academia and industry (Lin et al., 2023; Ma, 2025).

Recommendations based on collaborative filtering methods that analyze the similarity of users or items are an early strategy used for the recommendation of learning resources (Lee et al., 2017). However, such approaches model user–item interactions in a static way, ignoring the dynamic nature of user preferences and the dependencies between behaviors during the learning process (Premalatha et al., 2022). Session sequences can address changes in user preferences, yielding promising results across many domains and driving the development of multiple sequential recommendation models (Saraswat & Srishti, 2022). Most existing models employ recurrent neural networks (RNNs) to build session-based recommender systems, achieving satisfactory results (Kumar & Kumar, 2024; Zhang et al., 2021). Although RNN-based recommendation methods rely on sufficient user behavioral data to extract user representations, the behavioral data

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implied in session sequences are often limited, especially for newly enrolled users, for whom such data tend to be sparse. In addition, RNN-based methods may perform poorly when there is no dependency between neighboring actions, such as accidental clicks on the wrong item or joining a course out of curiosity; these actions lack clear contextual relationships (Wang et al., 2021). Sequential-based recommendation models perform well in handling temporal dependencies of user actions but have limitations in capturing complex transformational relationships between items and global contextual information.

In contrast, graph neural network (GNN)-based recommendation models can better capture complex transformational relationships between items and contextual information through graph structures, which have shown significant advantages in recommendation accuracy and diversity, and have received increasing attention (Pu et al., 2024; Xiong et al., 2024). However, unlike general resources, such as movies and music, there are inherent dependencies between learning resources (Hriez & Al-Naymat, 2021), of which prior learning dependencies are the most common. For example, the course Data Structures is clearly a prerequisite for Algorithm Design and Analysis, and data structures such as arrays, chain lists, and trees form the basis for the realization of various algorithms.

This study focuses on a relatively stable curriculum system, assuming that the logical dependencies among learning resources are relatively consistent within a given curriculum structure. This assumption reflects many real educational application scenarios; that is, the prerequisite relationships and resource dependencies of courses are usually predefined at the course outline or teaching plan level and remain unchanged during the model training and evaluation process (Zhou & Wang, 2025). Logical dependencies necessarily impose constraints on learning resource recommendations, and only after the prerequisite course is completed can subsequent courses be recommended (Sun et al., 2024). However, traditional recommender systems often assume that recommended objects are independent of each other, ignoring the existence of logical dependencies (Dong et al., 2024a). In educational scenarios, diverse dependencies are common among learning resources, and most existing recommendation algorithms based on GNNs do not take into account inherent logical dependencies between learning resources, resulting in insufficiently explored correlations in the data and reduced accuracy and relevance of recommendations (Chen et al., 2025).

To address the problems of missing logical dependencies inherent in learning resources and insufficient global context in sequential recommendation, this study proposes a unified learning resource recommendation method (ULRRM) that integrates multidimensional graph information to capture both logical and behavioral dependencies among resources and enhance the semantic richness of resource representation. As shown in Figure 1, the model consists of two main components. The first is resource dependency learning (RDL), which is dedicated to automatically mining the logical dependencies between resources and generating dependency representations by analyzing prior modification relationships and the logical order among resources. The second is sequence representation enhanced by a local–global dual view to capture complex behavioral relationships between resources using local session information and global context information and is denoised with a sparse attention mechanism. On this basis, the logical dependency representation is incorporated into the sequential recommendation model to improve the practical feasibility of the recommendations.

The main contributions of this research are as follows:

This study proposes a unified representation and dependency mining method for diverse learning resources. Through dependencies between concepts, it further deduces the logical dependencies between resources and extracts the corresponding dependency representations, thereby significantly enhancing the

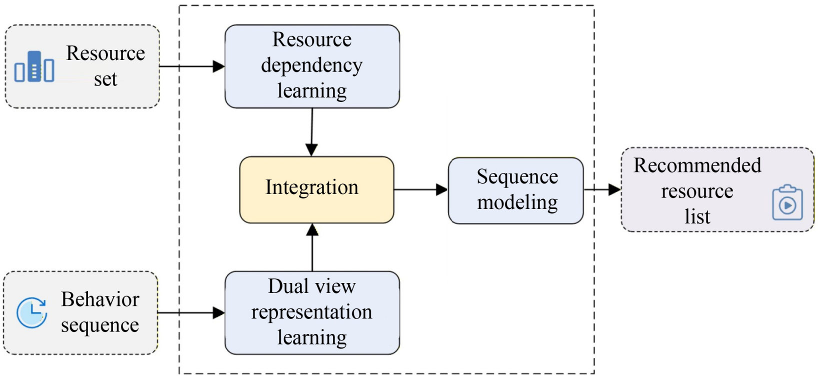


Figure 1 Simple framework of unified learning resource recommendation method.

potential connections between learning resources. Based on this, logical dependencies are incorporated into the sequential recommendation model.

To further mine contextual information and interest transitions in session history, this study models both local and global perspectives, learning behavior-dependent representations via GNN-based local and global modules, respectively, and mining session-level and global contextual information to enhance the learned representations. In addition, a sparse attention mechanism is introduced to minimize interference from irrelevant items in the session on recommendations.

Comprehensive experiments on real datasets show that ULRRM enhances sequential recommendation by integrating multidimensional graph information and outperforms classical and state-of-the-art models on several key metrics. Further analysis confirms the effectiveness of the proposed approach in improving the performance of learning resource recommendation models.

The rest of the paper is organized as follows. Section 2 briefly reviews related work. Section 3 describes the ULRRM method proposed in this study in detail. Section 4 presents extensive experiments on real datasets, comprehensive performance comparisons with existing state-of-the-art and classical recommendation methods, and visual analysis. Section 5 summarizes the findings and discusses the limitations of the proposed approach, as well as future work.

2 Related work

In this section, we briefly review the existing work on learning resource recommendation. Then, we present the classical paradigm for sequential recommendation methods as well as work related to the representation of learning resources.

2.1 | Learning Resource Recommendation

Among various learning resources, courses provide structured and systematic approaches to acquiring knowledge (Aljunid et al., 2025). Course recommendation has gained significant attention in recent years (Bhatt et al., 2024; Wu et al., 2024).

Traditional content-based or collaborative filtering methods make recommendations according to users' static preferences. To capture the dynamics of these preferences, researchers tend to model users' sequential behavior, which clearly helps improve the accuracy of recommendations. For example, Liang (2025) proposed a deep learning-driven course recommendation system based on gated recurrent units and constructed a time-sensitive modeling framework for student behavior that addresses the bottleneck of traditional recommendation models in long-term reliance modeling. Volk et al. (2020) proposed an RNN-based method to explore how the temporal sequence of courses affects student grades and facilitates course planning for college students. Chen and Ye (2024) utilized a bidirectional recurrent neural network model to obtain contextual semantic features of embedded courses and dynamically allocated weights through an attention mechanism, thereby enhancing the effectiveness of the course recommendation model.

Another line of research incorporates additional side information from users or resources. For example, Ren and Wu (2023) simulated long short-term memory, including repeated time-point marking and event repetition, demonstrating that the correlation between user behavior and occurrence time can significantly enhance model performance. Tian and Liu (2021) tracked users' learning capacity and integrated it into an online course recommendation system to enhance model performance. Gong et al. (2020) constructed a heterogeneous information network based on various entities—such as students, concepts, courses, videos, and teachers—and further proposed the attention heterogeneous graph convolutional deep knowledge recommender ACKRec. However, dependencies among resources are somewhat ignored, so the recommendations may be infeasible in practice (Zhao et al., 2020).

2.2 | Sequential Recommendation

Sequential recommendation takes as input a user–item interaction sequence and learns the item transition patterns hidden within it (Levy et al., 2023). From a technical perspective, sequential recommendation methods can be divided into three main categories: Markov chains, latent representations, and deep neural networks.

Traditional methods are built on Markov chains. The central task is to learn the transition probability underlying the sequence of interactions. Due to the limitations of Markov chains, these methods have difficulty in capturing long-term or higher-order dependencies (Wang et al., 2022a).

The rationale of latent representation methods is that implicit relations (e.g., dependencies) may emerge if objects are properly mapped into a latent space. Hence, they are committed to learning latent representations for users and items. Latent factor-based methods (Liang et al., 2016) decompose the observed interaction transition matrix into latent vector representations that are susceptible to data sparsity. Distribution representation-based methods (Wang et al., 2018) embed interactions into a low-dimensional space to learn the latent distribution. Although simple and efficient, these methods are not designed to handle ordered or heterogeneous sessions (Wang et al., 2022a).

Deep neural network models have been dominant in sequential recommendation in recent years (Deeva et al., 2022). GNNs are a promising direction due to their strength in modeling complex transitions between items. For example, they achieve outstanding performance in session-based recommendation (Wu et al., 2019). In addition to session-level information, Wang et al. (2020) further exploited global context (e.g., global neighbor information) to improve recommendation. Nevertheless, introducing a global context into the system may increase the risk of noise and overfitting. Furthermore, other studies have explored heterogeneous graphs for recommendation (Wang et al., 2024a). Zhang et al. (2026) enhanced course recommendation by meta-path sampling in heterogeneous networks and improved recommendation accuracy by integrating users' multi-interaction semantic information. They utilized the varied relationships and entities in education to construct heterogeneous graphs, on which GNNs were employed to enhance the model. However, challenges remain in effectively managing complexity and integrating domain knowledge.

2.3 | Representation Learning of Resources

In recent years, various representation learning methods have been proposed to enhance recommendation performance (Dong et al., 2024b). For instance, some studies have employed RNNs to learn representations of user preferences, although they face challenges related to long-term dependencies. Others have utilized autoencoder techniques for representation learning, but such methods can be sensitive to noise and constrained by assumptions about data distributions. In addition, some studies have utilized GNNs or large language models to learn representations of user–item interactions (Wang et al., 2024b; Zha et al., 2026). While some of these studies captured item representations by considering complex behavioral dependencies in sessions in sequential models (as discussed in Subsection 2.2), they often neglected logical dependencies.

Existing studies on learning dependency relations in educational data can be broadly divided into explicit dependency modeling and implicit dependency modeling approaches. Early representative research focused on explicitly identifying prerequisite relations using statistical measures or supervised learning methods, such as reference distance-based metrics (Liang et al., 2015) and feature-driven classifiers (Pan et al., 2017). These methods provide interpretable dependency structures but often rely on handcrafted features or static assumptions, limiting their scalability and adaptability.

More recent studies have tended to implicitly capture dependency information through representation learning frameworks, including GNNs and sequential models (Nakagawa et al., 2019; Shin et al., 2021), in which relational patterns are encoded into latent representations rather than explicitly constructed graphs. Such approaches have been widely adopted in educational recommendation and knowledge tracing tasks, demonstrating strong predictive performance (Ghosh et al., 2020). However, learned dependencies are often implicit, entangled with behavioral signals, and difficult to interpret or control (Guo et al., 2025).

It should be noted that the literature focuses on predicting concept-level dependency. In contrast, learning resource recommendation works on learning resources—such as courses and exercises—that are of coarser granularity than concepts. Hence, methods should be proposed to mine resource-level dependencies.

3 Methodology

In this section, we introduce the proposed ULRRM in detail. Figure 2 shows the overall architecture of ULRRM, which is mainly composed of three core modules: RDL, context-enhanced resource representation, and resource recommendation incorporating multidimensional graph information. First, in the RDL module, concept maps are used as a unified intermediate language to standardize the representation of multiple types of learning resources. Through concept map learning, partially observable premise relationships are used to capture logical relationships among resources.

Resource representations are then obtained and enhanced with multidimensional graph information derived from the construction of local, global, and dependency graphs. Local representations originate from the current session, while global resource representations span all sessions, allowing for resource crossover between sessions to enhance contextual information. The dependency graph is built based on resource dependencies to learn the dependency representations between resources. More comprehensive resource representations are obtained through representation learning of multidimensional graphs.

Finally, sequential representation of the current session is obtained by integrating multidimensional graph representations, and a sparse attention mechanism is used to aggregate the representations according to item importance, thus representing user preferences in the current session and incorporating rich contextual information. Resource recommendation is

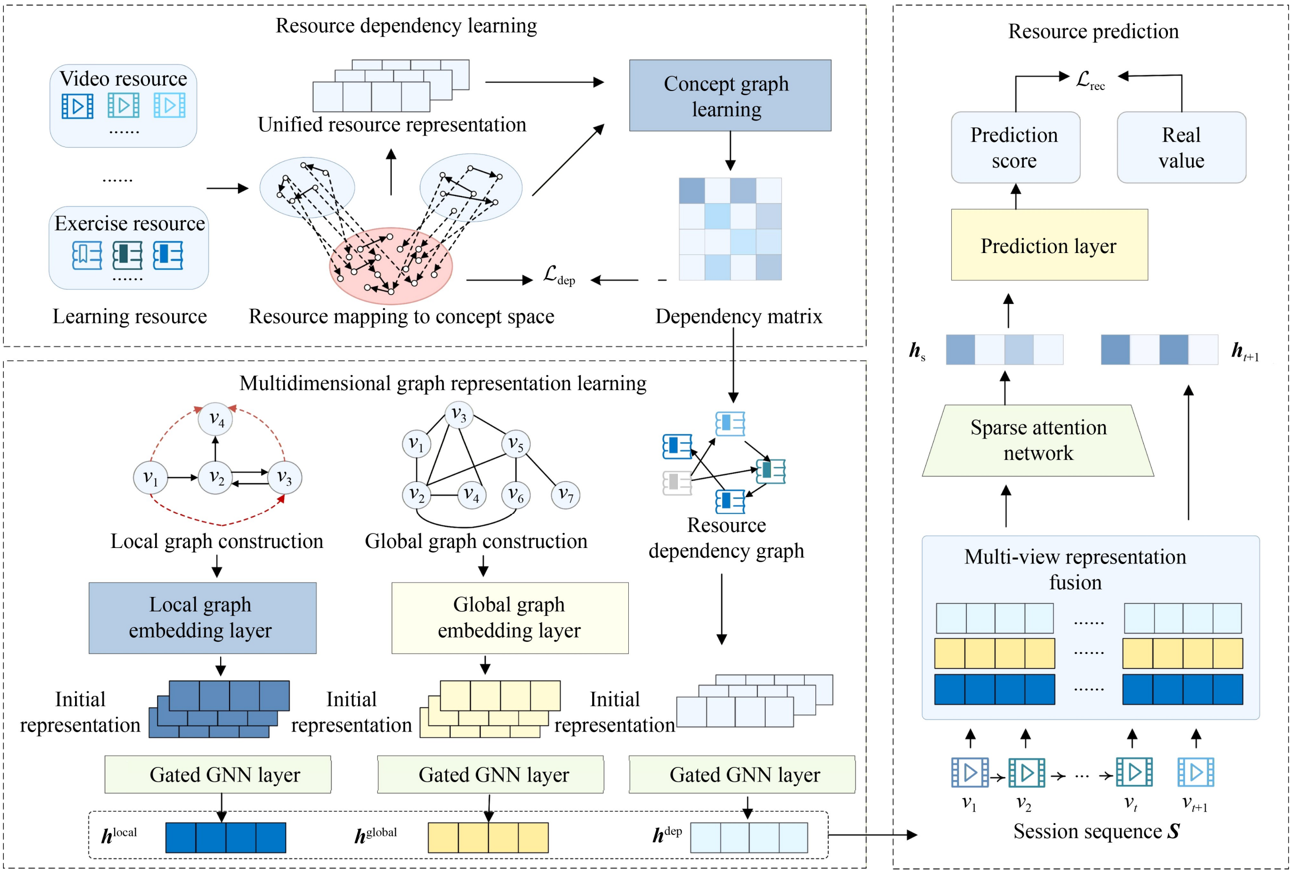


Figure 2 Workflow of the unified learning resource recommendation method. GNN: graph neural network.

achieved based on the similarity between sequential representation and candidate resource representations.

3.1 | Problem definition

Definition 1 (resource dependency prediction). Let $\boldsymbol{U}$ denote the set of learners and $\boldsymbol{R}$ represent the set of learning resources. The dependency relationships between resources are modeled as a directed graph $G = (\boldsymbol{R}, \boldsymbol{E})$, where vertices correspond to resources and edges $e_{ij} = (v_i \rightarrow v_j)$ indicate that resource v_j depends on v_i (e.g., as a prerequisite). Given a subset of known dependencies $E_{\text{known}} \subset \boldsymbol{E}$, resource dependency prediction is to predict the complete edge set $\boldsymbol{E}$ through link prediction by learning a mapping function $\varphi\colon \boldsymbol{R} \times \boldsymbol{R} \rightarrow [0,\ 1]$ that estimates the probability of the existence of unobserved edges.

Definition 2 (learning resource recommendation). Given a set of students $\boldsymbol{U}$, a collection of learning resources $\boldsymbol{R}$, and a set of resource types $\boldsymbol{T}$ (e.g., video, audio, and exercises). For each learner $u \in \boldsymbol{U}$, the interaction history with resources of type $\tau \in \boldsymbol{T}$ is represented as a session sequence: $\boldsymbol{S} = (v_1, v_2, \ldots, v_t)$. The learning resource recommendation task aims to predict $v_{t+1} = \text{argmax}_{v \in \boldsymbol{R}} P(v|\boldsymbol{S})$, where $P(v|\boldsymbol{S})$ estimates the probability that learner u will interact with resource v as their next engagement.

3.2 | Resource Dependency Learning

We use conceptual space as an intermediate language in the unified representation of resources and then perform conceptual graph learning to predict dependencies between resources.

3.2.1 Unified Resource Representation

Diversified learning resources are carriers of specific knowledge concepts, and each resource covers one or more knowledge concepts (Gong et al., 2020). Drawing on the idea of the bag-of-words model, which represents a sentence as a collection of words, this study maps resources to a more detailed conceptual level and uses conceptual space as a common feature space to obtain a unified representation of different types of resources. There is a many-to-many mapping relationship between resources and concepts. Therefore, an overall relationship diagram of concepts and resources at two different levels in the multiscale dependency reasoning framework is naturally formed, as shown in Figure 3.

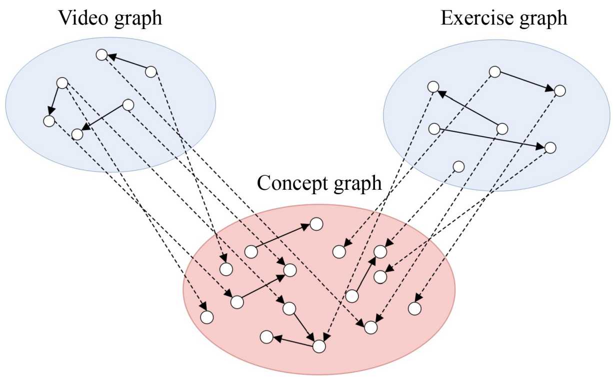


Figure 3 Schematic diagram of resource–concept mapping.

The set of resources can be represented as a matrix $\boldsymbol{X} \in \mathbb{R}^{n \times p}$, where n is the number of resources; p is the dimension of the general concept space; each row of the matrix corresponds to the conceptual representation of each resource; $\boldsymbol{Y}$ is an $n \times n$ matrix, where each unit represents the binary relationship between resources i and j; and $y_{ij} = 1$ indicates that resource i is the precursor of resource j, otherwise $y_{ij} = 0$. In this way, resource-dependent learning can be transformed into a link-prediction problem in conceptual space.

3.2.2 Resource Dependency Prediction

The challenge is that the underlying dependencies between concepts are unknown, so we sampled a small set of resource pairs O and domain experts annotated whether there is a dependency between each pair of resources based on professional knowledge. Labels were then used to predict potential dependencies between concepts.

The link prediction score between resources i and j can be expressed as $\hat{y}_{ij}$:

$$\hat{y}_{ij} = f_{\boldsymbol{B}}(\boldsymbol{x}_i, \boldsymbol{x}_j) = \boldsymbol{x}_i^{\mathrm{T}} \boldsymbol{B} \boldsymbol{x}_j, \tag{1}$$

where $\boldsymbol{B}$ is a $p \times p$ matrix, each element represents the weight of the directed connection between concept pairs, and the goal of concept graph learning is to optimize the model parameter matrix $\boldsymbol{B}$ according to the objective function (Eq. (2)). $\boldsymbol{x}_i^{\mathrm{T}} \boldsymbol{B} \boldsymbol{x}_j$ represents the sum of weights of all paths in the graph from node i to node j.

The objective function of the learning stage of the resource dependence relation is defined as

$$\mathcal{L}_{\text{dep}} = \min_{\boldsymbol{B}} \sum_{(u,v)\in O} \left(1 - y_{uv}\left((\boldsymbol{x}_u)\boldsymbol{B}\boldsymbol{x}_v^{\mathrm{T}}\right)\right)^2 + \frac{\lambda}{2}\|\boldsymbol{B}\|_{\mathrm{F}}^2, \tag{2}$$

where the first term maximizes the consistency of the predicted and true values, the second term is the regularization term where $\|\boldsymbol{B}\|_{\mathrm{F}}$ denoting the Frobenius norm to prevent overfitting, and λ is the hyperparameter.

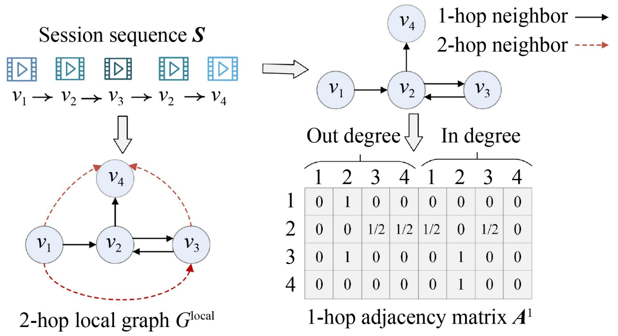
In this way, the weights of directed connections between all concept pairs are obtained, and since all resource representations are mapped to a unified concept space, the dependencies between resources in the test set can be predicted by Eq. (1). The dependency matrix between resources provides the basis for constructing the dependency graph.

3.3 | Multidimensional Graph Representation Learning

In this section, we construct a multidimensional graph of resources and extract node representations based on GNN to incorporate valuable global contextual information.

3.3.1 In-Session Local Information Learning

Following the settings in SR-GNN (Wu et al., 2019), a local graph G^{local} is built for the session $\boldsymbol{S}$. G^{local} is a directed graph; its set of vertices $\boldsymbol{R}^{\text{local}}$ is a subset of the set of resources $\boldsymbol{R}$, and the edges are denoted as adjacent within the session, as shown in Figure 4. Because resources may recur in a sequence of sessions, the normalized weight of each edge is computed by defining the number of occurrences of an edge divided by the out-degree of the starting node of that edge. The gated GNN is then applied to G^{local} to learn the local representation $\boldsymbol{h}_v^{\text{local}} \in \mathbb{R}^d$.



	Out degree				In degree			
	1	2	3	4	1	2	3	4
1	0	1	0	0	0	0	0	0
2	0	0	1/2	1/2	1/2	0	1/2	0
3	0	1	0	0	0	1	0	0
4	0	0	0	0	0	1	0	0

Figure 4 Construction of the local graph.

However, the 1-hop neighbor-based aggregation approach can aggregate only directly adjacent node representations, which is insufficient for learning the multi-hop neighbor context. Therefore, a multi-hop diffusion mechanism (Figure 4) is designed with a hop count of 2, for example, where each node will be directly connected to its second-order neighbors, which, on the one hand, takes into account all the possible paths between connected nodes to enhance the model's ability to learn the graph structure and, on the other hand, enhances the ability to capture the relationships between nodes that are not directly connected.

Specifically, the m-order adjacency matrix $\boldsymbol{A}_m$

is constructed according to the respective session graph, the graph structure information corresponding to different hop counts is preserved, the respective m-order local embedding representations of the nodes are learned, and dynamic aggregation is performed to obtain the final session-level node vector representation $\boldsymbol{h}_v^{\text{local}}$.

Ultimately, the local representation of any resource $v \in \boldsymbol{R}$ is defined as

$$\boldsymbol{h}_v^{\text{local}} = \sum_{n=1}^{N} \sum_{m=1}^{M} \boldsymbol{h}_v^{m,n},$$

where $m \in [1, M]$ is the number of hops of the aggregated neighbors and $n \in [1, N]$ denotes the number of independent sessions of the student.

The advantage of introducing the multi-hop diffusion mechanism lies in two aspects. On the one hand, it expands the neighborhood receptive field of a single layer of the GNN, thus lowering the risk of gradient disappearance. On the other hand, it reduces high-frequency noise due to the low-pass effect.

3.3.2 Global Context Representation Learning

In this subsubsection, we obtain the global representation of a resource node through global graph construction and global representation learning.

Construction of the global graph. To generate a global representation of the resource, we construct an undirected global graph G^{global} for all sessions in the dataset, with the vertex set $\boldsymbol{R}$, and create an undirected edge between each node and its m-hop neighbors. A simple schematic is shown in Figure 5. The weights in the global graph are then computed based on the number of edges and the distance between items. The initial weight $w_{(v_t, v_{t+m})}$ of each edge is set to 0. For each item $v_t \in \boldsymbol{S}$, its m-hop neighboring nodes in all sessions update the weight of the corresponding edge to $w_{(v_t, v_{t+m})} = w_{(v_t, v_{t+m})} + 1/m$, where m denotes the number of hops separated between v_t and v_{t+m} in the sequence. The weights are then normalized:

$$w_{v_t, v_{t+m}} = \hat{w}_{v_t, v_{t+m}} \left(\frac{1}{\deg(v_t)} + \frac{1}{\deg(v_{t+m})} \right), \tag{3}$$

where $\deg(v_t)$ refers to the degree of v_t in G^{global}.

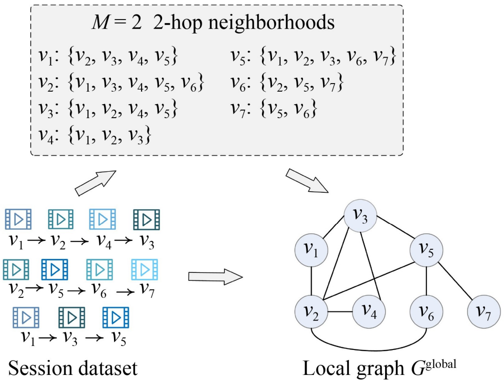


Figure 5 Construction of the global graph.

Global representation learning. In this section, we design an L-layer GNN to generate global representations of the resources, where L is a hyperparameter. Each item $x \in \boldsymbol{R}$ is encoded into a unified embedding space; that is, $x \in \mathbb{R}^d$. The initial embedding x is based on 1-hot encoding and is then transformed into a d-dimensional latent vector space using the trainable matrix $\boldsymbol{W}_0 \in \mathbb{R}^{d \times |R|}$.

For any $0 \leqslant l < L$, layer $l+1$ transforms the output of layer l ($\boldsymbol{h}_v^{\text{global}_{(l)}}$) in two steps.

Step 1: Neighborhood aggregation. To differentiate the importance of the neighboring nodes, a session-aware attention mechanism is used to aggregate the neighboring context representation of the nodes. In general, the item that is closer to the current session preference is more important for recommendation, so the importance level can be computed from the current session features:

$$\widetilde{\pi}(u, v) = \boldsymbol{q}^{\text{T}} \sigma(\boldsymbol{W}_{uv}[(\boldsymbol{h}_S^{(l)} \odot \boldsymbol{h}_u^{\text{global}_{(l)}}) || w_{uv}]), \tag{4}$$

where σ represents an activation function; $\boldsymbol{h}_S^{(l)}$ denotes the characteristics of the current session, computed from the average of all item representations in the session; and $\boldsymbol{W}_{uv}$ and $\boldsymbol{q}$ are learnable parameters. The operator "$\odot$" refers to the Hadamard product of vectors, while "$||$" denotes concatenation. Then, the importance coefficients $\widetilde{\pi}(u, v)$ of all neighbors connected to node v are normalized using the softmax function to obtain $\pi(u, v)$, the normalized attention weight of neighbor u with respect to node v.

Finally, the neighborhood context representation of a node is obtained by linearly combining neighboring nodes based on the session-aware attention score:

$$\boldsymbol{\eta}_v^l = \sum_{u \in N_v} \pi(u, v) \boldsymbol{h}_u^{\text{global}_{(l)}}, \tag{5}$$

where N_v is the neighborhood of v in G^{global}.

Step 2: Representation update. For any $v \in \boldsymbol{R}$, combining the node representations of the layer l with the aggregated neighborhood information yields the node representations of the layer $l+1$:

$$\boldsymbol{h}_v^{\text{global}_{(l+1)}} = \sigma(\boldsymbol{W}_{h\eta}[\boldsymbol{h}_v^{\text{global}_{(l)}} || \boldsymbol{\eta}_v^l]), \tag{6}$$

where $\boldsymbol{W}_{h\eta}$ is a learnable parameter.

In the above manner, the aggregator can be extended from one layer to multiple layers to further explore the higher-order connectivity information of the graph and merge more information related to the current session into the current representation.

For notational simplicity, $\boldsymbol{h}_v^{\text{global}_{(l)}}$ is denoted simply as $\boldsymbol{h}_v^{\text{global}}$.

3.3.3 Dependency Graph Representation Learning

Given that the dependency relationships among learning resources naturally form graph-structured data—that is, resources correspond to graph nodes and the directed dependency relationships among resources correspond to the directed edges in the graph, which has a very similar structure to the global graph constructed by the global module in the sequential recommendation basis model—the structure of the global module can be borrowed to construct the static dependency graph G^{dep} based on the dependency relationship matrix. The same GNN structure as the global representation learning layer is adopted to learn the static dependency relationship representation $\boldsymbol{h}_v^{\text{dep}}$ of the resources. The process is shown in Figure 6.

3.4 | Resource Recommendation with Multidimensional Representation

In this section, we integrate the resource representation from the multidimensional graph and consolidate the representation of the session sequence accordingly for resource prediction.

3.4.1 Multidimensional Representation Fusion

The in-session and inter-session representations learned from the local module and the global module, respectively, are added as the dynamic features at the sequence level and then connected to the resource dependency representation $\boldsymbol{h}_v^{\text{dep}}$, and a linear transformation is performed to obtain the final hybrid embedding representation $\boldsymbol{h}_v$.

First, for any resource $v \in \boldsymbol{S}$, the final representation of v is defined as

$$\boldsymbol{h}_v = \boldsymbol{W}_{gld}[(\boldsymbol{h}_v^{\text{local}} + \boldsymbol{h}_v^{\text{global}})||\boldsymbol{h}_v^{\text{dep}}], \tag{7}$$

where the matrix $\boldsymbol{W}_{gld} \in \mathbb{R}^{d\times 2d}$ is a learnable parameter, which is used to compress the two combined embedding vectors into the latent space $\mathbb{R}^d$.

Then, we apply the feed-forward network to inject more nonlinearity into the representations:

$$z_v = \sigma(\boldsymbol{W}_{hv}\boldsymbol{h}_v + \boldsymbol{b}_{hv}), \tag{8}$$

where $\boldsymbol{W}_{hv}$ and $\boldsymbol{b}_{hv}$ are learnable parameters.

The final representation $\boldsymbol{h}_S$ can be obtained by weighted averaging of the node representations in the session. The weights should be properly defined to weaken the effects of interest offset and noise pollution.

We use entmax$_\alpha$ attention (Peters et al., 2019) of $\alpha = 2$ in the attention mechanism (i.e., sparsemax) to steepen the smooth curve so that the items with less weight are directly mapped to 0, reducing the negative impact of unrelated items. The attention weight can be expressed as follows:

$$\beta_v = \text{sparsemax}(\boldsymbol{q}_1^{\text{T}}\sigma(\boldsymbol{W}_{zv}z_v + \boldsymbol{W}_{hs}\boldsymbol{h}_S' + \boldsymbol{b}_{\beta v})), \tag{9}$$

where $\boldsymbol{h}_S'$ is obtained by directly averaging the node representations in the session and $\boldsymbol{W}_{zv}, \boldsymbol{W}_{hd}, \boldsymbol{q}_1, \boldsymbol{b}_{\beta v} \in \mathbb{R}^d$ are learnable parameters.

Finally, we obtain the sequential representation of $\boldsymbol{S}$:

$$\boldsymbol{h}_S = \sum_{v\in \boldsymbol{S}} \beta_v \boldsymbol{h}_v. \tag{10}$$

3.4.2 Learning Resource Prediction

The goal of learning resource prediction is to predict the next resource, s_{n+1}, given a session $\boldsymbol{S} = s_1 s_2 \cdots s_n$. Our prediction is based on the similarity of $\boldsymbol{h}_S$ to the representation x_v of any resource v, with softmax as the activation function. Specifically, the probability that $s_{n+1} = v$ is predicted to be

$$\hat{y}_v = \text{softmax}(\boldsymbol{h}_S^{\text{T}} x_v). \tag{11}$$

In the model training phase, the loss is defined as the cross-entropy of the predicted values with the

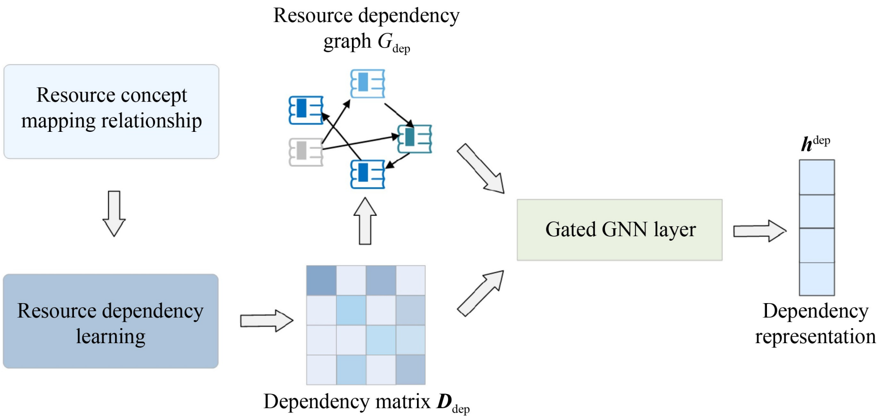


Figure 6 Dependency graph representation learning process.

ground truth. Suppose the ground truth of session $\boldsymbol{S}$ is $s_{n+1}=v$. $y_u=1$ if $u=v$, and $y_u=0$ for any $u\in\boldsymbol{R}\setminus\{v\}$. The loss is defined as

$$\begin{aligned}\mathcal{L}_{\text{rec}}&=-\sum_{u\in\boldsymbol{R}}\left(y_u\log\left(\hat{y}_u\right)+\left(1-y_u\right)\log\left(1-\hat{y}_u\right)\right)\\&=-\log\left(\hat{y}_v\right)-\sum_{u\in\boldsymbol{R}\setminus\{v\}}\log\left(1-\hat{y}_u\right).\end{aligned}\tag{12}$$

The algorithm is shown in Electronic Supplementary Material.

4 Experiments

In this section, extensive experiments are conducted on real datasets to evaluate the performance of the proposed ULRRM method.

4.1 Datasets

The effectiveness of the proposed method was verified on the real dataset MOOCCube (Yu et al., 2020). MOOCCube is a comprehensive large-scale MOOC dataset that includes 706 online courses, 38,181 teaching videos, hundreds of thousands of course registration records, and video watching records from 199,199 users. The concept terms and entity description data come from Baidu Baike and Wikipedia, and the course data and student behavior data come from the real learning environment of XuetangX.

The MOOCCube dataset is divided into MOOCCube_course and MOOCCube_video. Performance is evaluated on both subsets to evaluate resource recommendation across different levels of granularity.

As in SR-GNN (Wu et al., 2019), we removed resources that appeared fewer than five times and sessions of length 1. For each of the remaining sessions $\boldsymbol{S}=(s_1s_2\cdots s_n)$, we adopt the Leave-One-Out Cross-Validation method to generate sub-sequences $((s_1,s_2,\ldots,s_{k-1}),s_k),1<k\leqslant n$. We used the latest sample for testing, and the remaining samples for training.

To supervise concept graph learning, we manually marked whether or not a prerequisite relation existed for 232 pairs of MOOCCube courses. This was done by analyzing the course prerequisite descriptions using standard text processing techniques, such as stop-word removal, term frequency-based term weighting, and the removal of rare words.

In addition, to show that our techniques work even when dependency information is unavailable, we verified the sequential part of ULRRM (i.e., the module of globally enhanced GNN with sparse attention, abbreviated as ULRRM-seq) on MOOC2019 (Zhang et al., 2019).

MOOC2019 covers user-enrolled behaviors from October 1, 2016, to March 31, 2018 in XuetangX. The specific statistics of the datasets after preprocessing are shown in Table 1.

Table 1 Statistics of the datasets used in the experiments

Dataset	#clicks	#items	#train sessions	#test sessions	Average length
MOOCCube_course	682,753	681	406,455	44,723	3.26
MOOCCube_video	1,765,080	17,466	1,390,550	154,304	8.76
MOOC2019	458,452	912	343,264	31,341	5.54

4.2 Baselines

We selected classical traditional recommendation models and recently performed recommendation models as benchmarks, including three traditional recommendation models, four sequential recommendation models, and three graph-based sequential recommendation models. The models are described as follows:

(1) Traditional models

POP recommends the top-N frequent items in the training set.

Item-KNN (Sarwar et al., 2001) recommends items similar to the last item in the session.

BPR (Rendle et al., 2009) optimizes a pairwise ranking objective function in a Bayesian way.

(2) Sequential-based models

GRU4Rec (Hidasi et al., 2016) uses RNNs to model sessions for session-based recommendation.

STAMP (Liu et al., 2018) captures the user's general interest in the current session and current interest in the last click.

BERT4Rec (Sun et al., 2019) employs deep bidirectional self-attention to model user behavior for sequential recommendation.

LightSANs (Fan et al., 2021) introduces a low-rank decomposition self-attention mechanism to map users' historical behavior sequences into potential interests.

(3) Graph-based models

SR-GNN (Wu et al., 2019) uses GNNs to learn item and session representations for sequential recommendation.

GC-SAN (Xu et al., 2019) combines GNNs and self-attention networks for sequential recommendation.

DGNN (Li et al., 2023) utilizes dual GNNs to decouple explicit dependencies and implicit associations between items for session recommendation.

4.3 Experimental Settings

Parameter setup. Following previous methods (Xu et al., 2019), we set the dimension of latent vectors to 100 for both datasets. All parameters were initialized using a Gaussian distribution with a mean of 0 and a standard deviation of 0.1. We used the mini-batch Adam optimizer with an initial learning rate of 0.001, which decayed by 0.1 after every 3 epochs. The batch size and the L2 penalty were set to 100 and 10^5, respectively, and the neighborhood radius δ in constructing the global graph was set to 2.

Evaluation metrics. We followed the literature (Wu et al., 2019) and adopted two widely used ranking-based metrics for recommendation: P@N and MRR@N, where N is 10 or 20.

P@N (precision) measures the percentage of the ground truth instances that are successfully recommended in top-N positions in a ranking list. MRR@N (mean reciprocal rank) is the average of reciprocal ranks of the correctly recommended instances, which considers the order of recommendation ranking list.

4.4 | Performance Comparison

All baselines and our model were trained and evaluated on the same set. Note that the MOOC2019 dataset contains only the user–course registration sequence and does not support resource-dependent learning. Therefore, we used it only to verify the validity of the sequential part of ULRRM (named ULRRM-seq), which does not contain resource-dependent learning and the representation learning part of the dependency graph. Performance comparisons are shown in Tables 2 and 3.

Table 2 Performance comparison of ULRRM with other baseline methods on the MOOCCube dataset

Method	Performance score in MOOCCube_course				Performance score in MOOCCube_video			
	P@10	MRR@10	P@20	MRR@20	P@10	MRR@10	P@20	MRR@20
POP	0.1973	0.0621	0.3389	0.0755	0.0445	0.0171	0.0774	0.0198
BPR	0.2633	0.1059	0.3779	0.1147	0.1209	0.0354	0.1734	0.0452
Item-KNN	0.3559	0.1799	0.4765	0.1885	0.3093	0.1324	0.4189	0.1450
STAMP	0.2641	0.1126	0.3769	0.1203	0.6167	0.3811	0.6988	0.3868
BERT4Rec	0.3203	0.1427	0.4420	0.1510	0.6194	0.3835	0.7013	0.3893
GRU4Rec	0.4232	0.2064	0.5403	0.2144	0.6078	0.3784	0.6902	0.3856
LightSANs	0.4362	0.2351	0.5674	0.2377	0.6432	0.3970	0.7125	0.4133
SR-GNN	0.4649	0.2432	0.5825	0.2513	0.6456	0.4175	0.7186	0.4226
GC-SAN	0.4562	0.2367	0.5756	0.2449	0.6376	0.3836	0.7040	0.4112
DGNN	0.4730	0.2406	0.5742	0.2508	0.6511	0.3987	0.7210	0.4355
ULRRM	**0.4831**	**0.2533**	**0.5988**	**0.2581**	**0.6617**	**0.4308**	**0.7344**	**0.4359**

Notes. Underlined results repersent the best scores across all baseline models except ULRRM. The scores of ULRRM are in bold.

Tables 2 and 3 show that GNN-based sequential recommendation baselines (SR-GNN and GC-SAN) substantially outperformed other baselines. This indicates that sequential models and GNNs are suitable for learning resource recommendation. A possible reason for this is that sequential models inherently capture the dynamics of user preference in a session and that GNNs are capable of transforming items with complex relations. Our models—ULRRM and ULRRM-seq—outperformed both SR-GNN and GC-SAN on all datasets in all metrics, with an average improvement of over 4%.

Table 3 Performance comparison of ULRRM-seq with other baseline methods on the MOOC2019 dataset

Method	Performance score			
	P@10	MRR@10	P@20	MRR@20
POP	0.0951	0.0471	0.1503	0.0488
BPR	0.0859	0.0292	0.1308	0.0317
Item-KNN	0.2951	0.1345	0.3898	0.1363
STAMP	0.2421	0.1064	0.3418	0.1132
BERT4Rec	0.2344	0.0920	0.3447	0.0995
GRU4Rec	0.2492	0.1123	0.3483	0.1193
LightSANs	0.2876	0.1672	0.3754	0.1446
SR-GNN	0.3508	0.1705	0.4634	0.1783
GC-SAN	0.3160	0.1500	0.4354	0.1582
DGNN	0.3692	0.1677	0.4562	0.1822
ULRRM-seq	**0.3711**	**0.1826**	**0.4829**	**0.1904**

Notes. Underlined results repersent the best scores across all baseline models except ULRRM. The scores of ULRRM are in bold.

In conclusion, our model takes into account the dependencies between resources and the global context within session sequences in recommendation. In the comparative experiments, ULRRM achieved strong performance, and the results suggest that incorporating multidimensional graph information may be beneficial for improving recommendation effectiveness.

4.5 | Ablation Study

In the ablation experiment, to study the contribution of each module to the ULRRM, we compared the performance of three variants of the ULRRM obtained by deleting the modules one by one, which are outlined as follows:

ULRRM-w/o-dep: ULRRM without the module of RDL—namely, ULRRM-seq.

ULRRM-w/o-global: Removal of global graph learning based on ULRRM-w/o-dep.

ULRRM-w/o-local: Removal of in-session local information learning based on ULRRM-w/o-dep.

As shown in Table 4, performance declined with the reduction of modules. This suggests that each module contributes to the performance of ULRRM: The local module captures the dynamics of the users' preference in the session, the global module exploits the rich global context information, and dependency integration leverages the dependency relations that may support recommendation.

Table 4 Contributions of each module to the performance of ULRRM

Method	Performance score in MOOCCube_course		Performance score in MOOCCube_video	
	P@20	MRR@20	P@20	MRR@20
ULRRM-w/o-dep	0.5931	0.2567	0.7294	0.4312
ULRRM-w/o-global	0.5900	0.2557	0.7243	0.4259
ULRRM-w/o-local	0.5743	0.2448	0.7004	0.4054
ULRRM	**0.5988**	**0.2581**	**0.7344**	**0.4359**

Note. The scores of ULRRM are in bold.

To verify the effectiveness of the mechanism for fusing dependency information mentioned in Subsection 3.4, we designed two other ablation variants:

ULRRM-emb: Only the fusion at the node representation level is considered, and the learned resource dependencies are fused into the final embedded representation of the project.

ULRRM-att: Considering only the fusion at the attention coefficient level, the learned resource dependencies are integrated into the calculation of the importance attention coefficient of each item in the session representation.

The experimental results are shown in Figure 7. ULRRM, which considers both item embedding fusion and attention coefficient fusion, achieved the best performance. The variants ULRRM-emb and ULRRM-att fused only in either aspect, missing some dependency information. However, both were better than ULRRM-w/o-dep which does not consider resource dependency at all. The comparison confirmed the effectiveness of fusing dependency.

4.6 | Hyperparameters

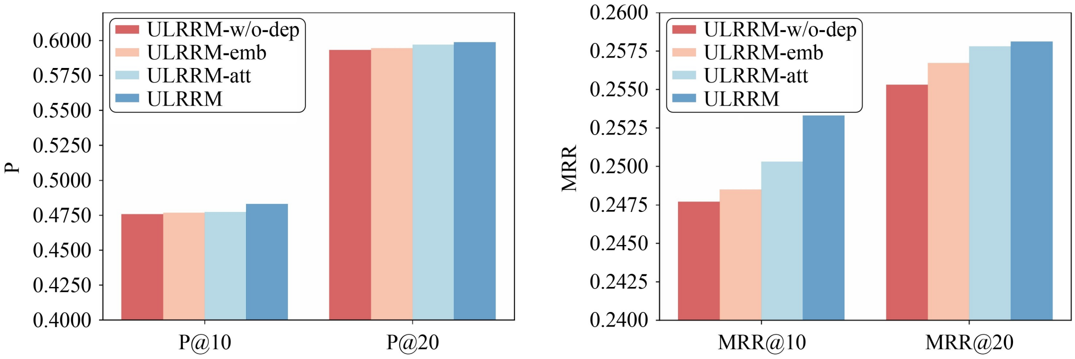
In this section, we begin by discussing the impact of two core hyperparameters—the number of neighbors and the number of hops—on model performance during GNN aggregation. The attention coefficients computed from two different transformation functions in α-entmax attention are then visualized.

Number of sampled neighbors. Considering the computational efficiency and the risk of overfitting, we sorted the neighboring nodes of each item into descending order of weight and kept only the first $N = \{4, 8, 12\}$ neighbors. Experiments were conducted on the MOOCCube_course and MOOCCube_video datasets, and the results are shown in Figure 8.

Figure 8 shows that the best performance was achieved when $N = 8$. This is because a value that is too small leads to insufficient global context information, while one that is too large leads to global information diluting local information. When N was increased from 8 to 16, performance decreased slightly. This suggests that introducing too much global context may introduce redundant or irrelevant information and also lead to over-smoothing of the representation. Therefore, in our model, N was set to 8.

Number of neighbor hops. The hop count of neighbors refers to the furthest neighbor hop that a node can access during the aggregation process of the GNN. Table 5 compares the two cases of hop count $M = 1$ and $M = 2$. It shows that the difference in performance was almost negligible (about 0.1%). This might be because a larger M helps capture high-order global information while bringing more noise.

Visualization of the attention coefficient. We further visualized the attention coefficients for different hyperparameter α values in entmax, as shown in Figure 9, where the vertical axis is labeled with 20 randomly selected sessions and the horizontal axis is labeled with the resources in the sessions. The rows represent a sample of sessions, and the columns represent the different interaction items in the session. The cells represent the level of interest of the item in the session; the higher the level of interest, the darker the color. Figure 9(b) has a stronger color contrast, which means that 2-entmax allocates attention in a more



(a) (b)

Figure 7 Analysis of the effectiveness of the fusion mechanism. (a) P@10 & P@20; (b) MRR@10 & MRR@20.

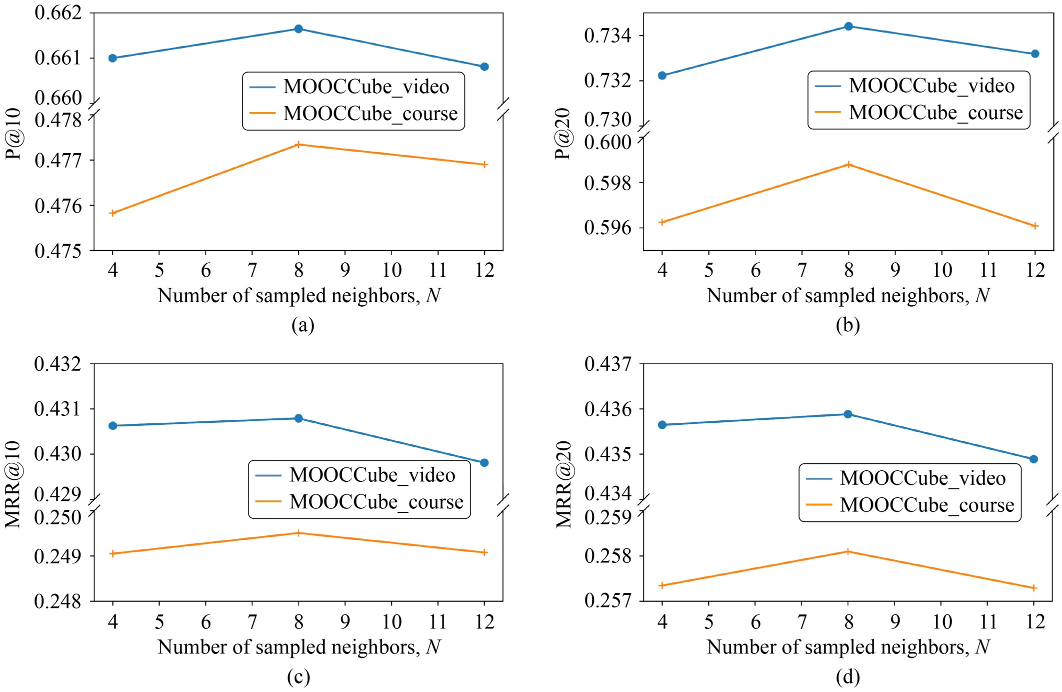


Figure 8 Performance for different numbers of sampled neighbors. (a) P@10; (b) P@20; (c) MRR@10; (d) MRR@20.

Table 5 Effect of parameter *M* (hops)

Method	Score in MOOCCube_course		Score in MOOCCube_video	
	P@20	MRR@20	P@20	MRR@20
1-hop	**0.5988**	**0.2581**	0.7338	0.4350
2-hop	0.5974	0.2576	**0.7344**	**0.4359**

Note. The higher scores are in bold.

focused way. The increased α brings more sparsity, which means that only a few items receive high attention, while the others receive low attention, and irrelevant or noisy items can be filtered to improve the recommendations.

4.7 | Case Study

Dependency prediction analysis. To further explore the reasonableness of the resource dependency prediction, some of the dependencies were extracted, the course IDs were converted to course names, and local dependencies were visualized, as shown in Figure 10. Among the computer courses shown, Advanced Language Programming and Data Structures were the prerequisites for most courses, and the prediction results were in line with general cognition in the context of realistic scenarios.

Resource recommendation analysis. In this section, a case from the recommended results is

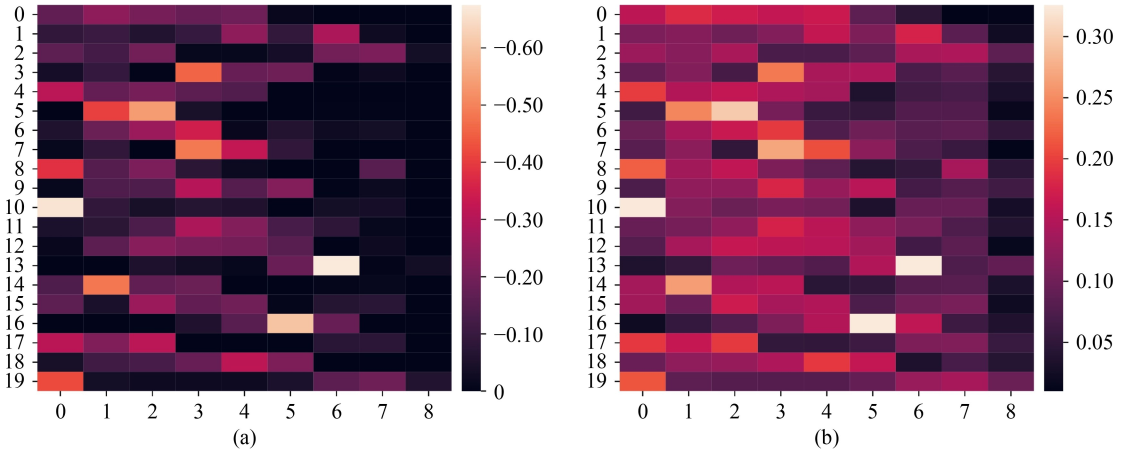


Figure 9 Visualization of the attention coefficient. (a) 1-entmax (equivalent to softmax); (b) 2-entmax (equivalent to sparsemax).

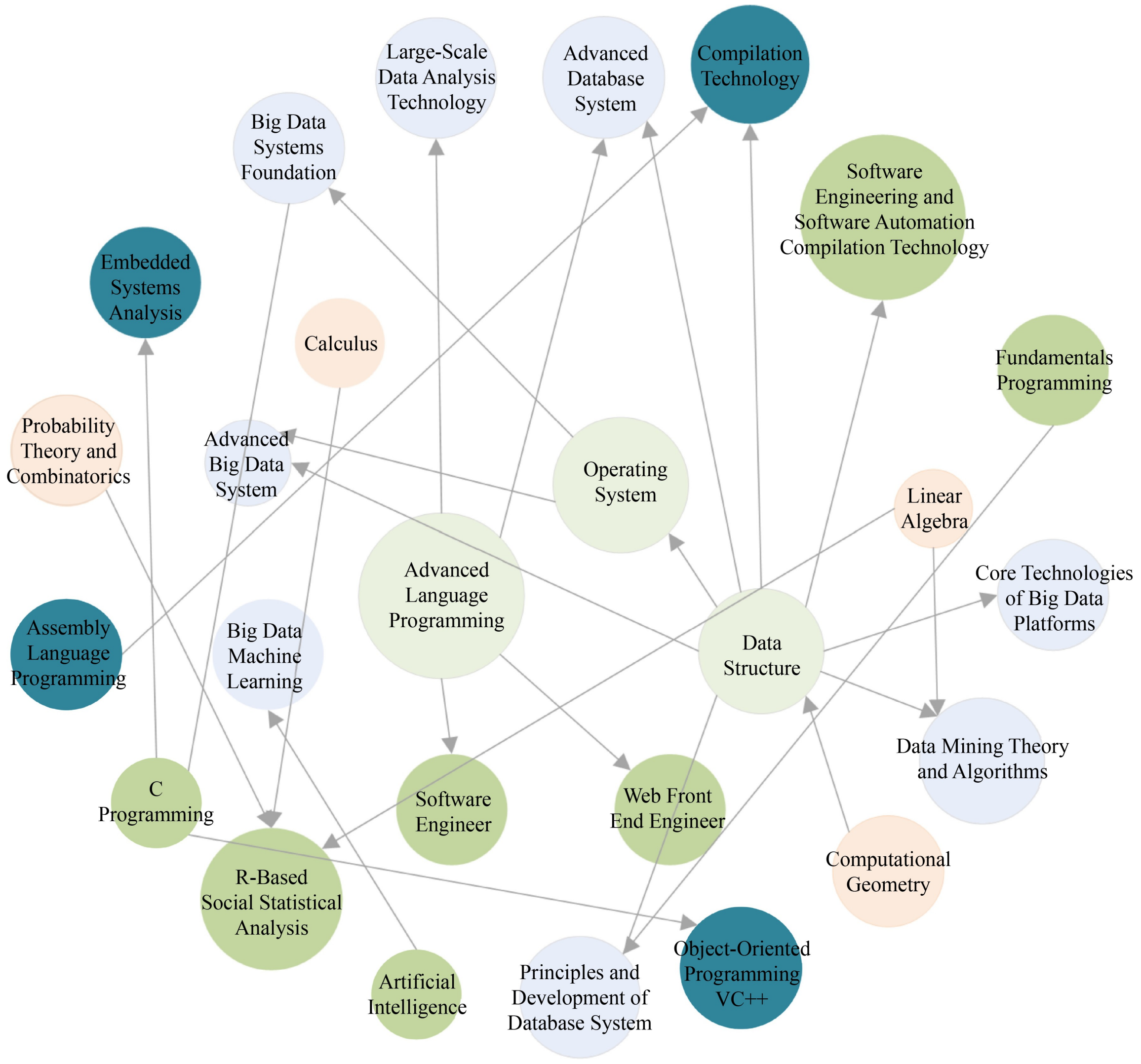


Figure 10 Visualization of the results of course–resource relationship projections (partial).

analyzed to demonstrate the validity of the proposed ULRRM. We selected student U_10770703 in the MOOCCube_course dataset as the subject of analysis, who studied several courses, among which physics courses accounted for a large proportion. The learning history and ULRRM recommendations are shown in Figure 11. The dashed circle above the user sequence in the figure indicates the course resources that have a prerequisite dependency on the course resources that the user has interacted with historically, and the arrows indicate the prerequisite relationship. For example, Electrical Technology is a prerequisite for Fundamentals of Digital Electronics and Fundamentals of Analog Electronics. According to the recommendations of the ULRRM model in this study, the courses in blue on the list reflect the model's ability to learn the dependency characteristics of resources and can guide the user's learning path to a certain extent while recommending highly relevant resources according to the user's personalized preferences.

5 Conclusions

In this study, we proposed a ULRRM that enables the recommendation of different kinds of learning resources. Inspired by the bag-of-words model, knowledge concepts were used as an intermediate language to unify the representations of different learning resources and provide static structural semantics for multidimensional resource information acquisition. Specifically, dependencies between concepts were extracted through concept graph learning, which in turn predicted resource dependencies based on dependencies between concepts. Further, static resource representations were extracted based on resource dependency graphs, while local session graphs and global session graphs were built based on students' historical session information to introduce rich contextual information in terms of learning dynamic behavior. Ultimately, the

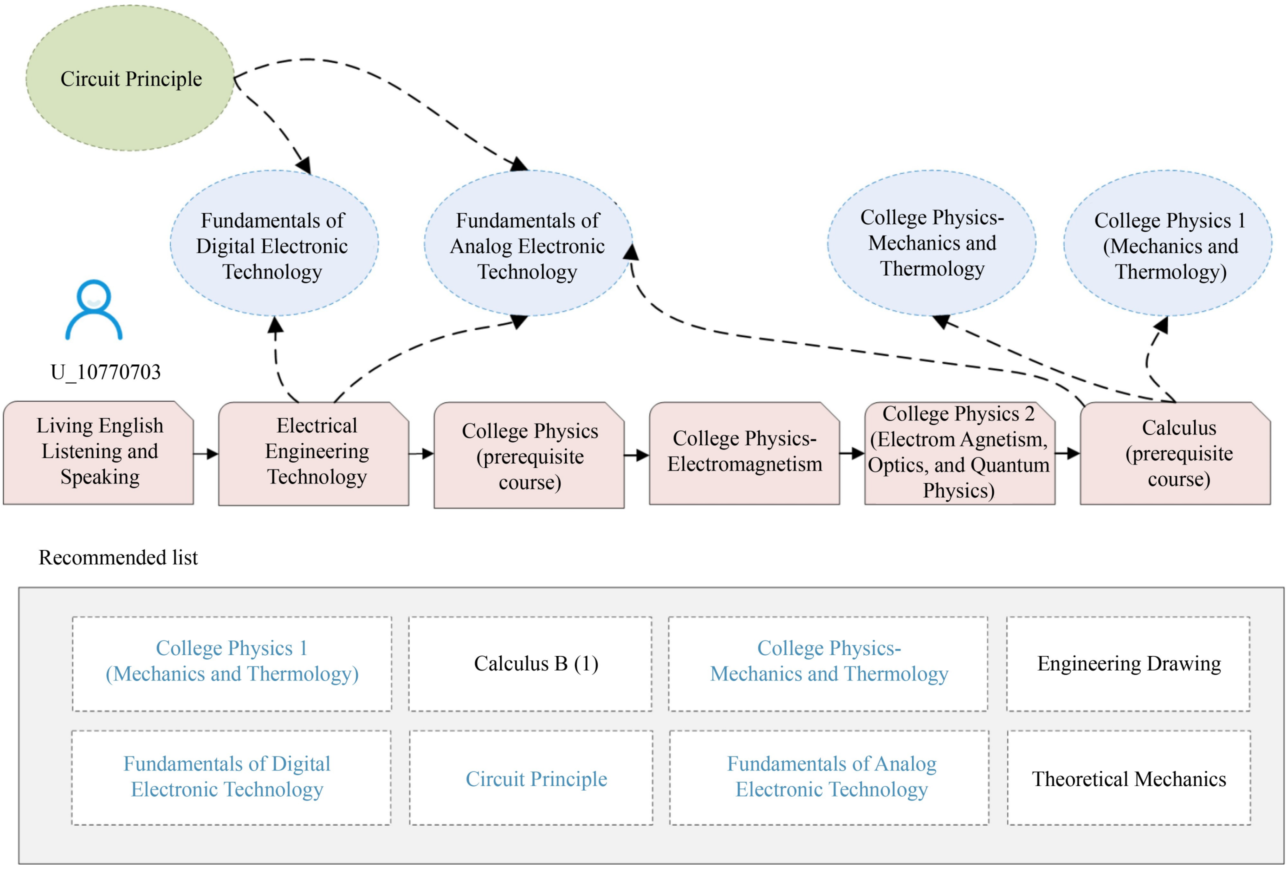


Figure 11 Visualization of the results of resource recommendation analysis (partial).

multidimensional resource representations were integrated, and sequence representations were obtained for resource recommendation by capturing student preferences through sparse attention and suppressing noise interference. We conducted extensive experiments on real datasets to validate the superiority of the proposed approach.

While this work demonstrates the effectiveness of dependency-aware representation learning for learning resource recommendation, several promising directions remain for future research. To better support online learning scenarios, future work will investigate model optimization strategies, such as incremental graph updates, parameter sharing across graph components, and efficient graph sampling, with the goal of improving scalability and real-time performance. In addition, incremental and continual learning strategies will be explored to progressively update dependency representations from accumulated interaction data, thereby enhancing robustness and reducing reliance on static annotations. To address data sparsity in GNN-based recommendation models, future studies will explore the use of large language models (LLMs) as data enhancers to generate potential learner–resource interactions, helping alleviate insufficient deep relationship learning. Meanwhile, by leveraging the generative capabilities of LLMs, we will investigate their potential role in producing semantic identifiers to enrich resource representations and improve the diversity of recommended content.

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References

Aljunid, M. F., Manjaiah, D. H., Hooshmand, M. K., Ali, W. A., Shetty, A. M., & Alzoubah, S. Q. (2025). A collaborative filtering recommender systems: Survey. *Neurocomputing*, *617*, 128718.

Bhatt, S. M., Van Den Noortgate, W., & Verbert, K. (2024). Investigating the use of deep learning and implicit feedback in K12 educational recommender systems. *IEEE Transactions on Learning Technologies*, *17*, 112–123.

Bobko, T., Corsette, M., Wang, M. J., & Springer, E. (2024). Exploring the possibilities of Edu-Metaverse: A new 3-D ecosystem model for innovative learning. *IEEE Transactions on Learning Technologies*, *17*, 1278–1289.

Chang, S. C., & Dao, N. D. (2026). An intelligent recommender system based on K-nearest neighbors to foster self-regulated learning and reduce cognitive load in online higher education. *Computers & Education*, *240*, 105470.

Chen, J., & Ye, W. Y. (2024). TB-BGAT with tinyBERT and BiGRU in personalized course recommendations. *International Journal of Information and Communication Technology Education*, *20*(1), 1–15.

Cen, Y., Jiang, S., Cai, W., & Cen, G. (2025). EGRec: A MOOCs course recommendation model based on knowledge graphs. *Discover Applied Sciences*, *7*(6), 578.

Deeva, G., De Smedt, J., & De Weerdt, J. (2022). Educational sequence mining for dropout prediction in MOOCs: Model building, evaluation, and benchmarking. *IEEE Transactions on Learning Technologies*, *15*(6), 720–735.

Dong, S., Tao, X. Y., Zhong, R., Wang, Z. F., Zuo, M. Z., & Sun, J. W. (2024a). Advanced mathematics exercise recommendation based on automatic knowledge extraction and multilayer knowledge graph. *IEEE Transactions on Learning Technologies*, *17*, 776–793.

Dong, Y., Liu, Y., Dong, Y., Wang, Y., & Chen, M. (2024b). Multi-knowledge enhanced graph convolution for learning resource recommendation. *Knowledge-Based Systems*, *291*, 111521.

Fan, X. Y., Liu, Z., Lian, J. X., Zhao, W. X., Xie, X., & Wen, J. R. (2021). Lighter and better: Low-rank decomposed self-attention networks for next-item recommendation. In: *Proceedings of the 44th International ACM SIGIR Conference on Research and Development in Information Retrieval*. Montreal: Association for Computing Machinery, 1733–1737.

Ghosh, A., Heffernan, N., & Lan, A. S. (2020). Context-aware attentive knowledge tracing. In: *Proceedings of the 26th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. San Diego: Association for Computing Machinery, 2330–2339.

Gong, J. B., Wang, S., Wang, J. L., Feng, W. Z., Peng, H., Tang, J., & Yu, P. S. (2020). Attentional graph convolutional networks for knowledge concept recommendation in MOOCs in a heterogeneous view. In: *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. Xi'an: Association for Computing Machinery, 79–88.

Guo, L. K., Zhang, J. Y., Ma, G. Z., & Dai, J. H. (2025). A deep knowledge tracing model based on cognitive assimilation and item response theory with better interpretability. *Applied Soft Computing*, *180*, 113331.

Hidasi, B., Karatzoglou, A., Baltrunas, L., & Tikk, D. (2016). Session-based recommendations with recurrent neural networks. *arXiv Preprint*, arXiv:1511.06939.

Hriez, R. F., & Al-Naymat, G. (2021). A framework to capture the dependency between prerequisite and advanced courses in higher education. *Journal of Computing in Higher Education*, *33*(3), 807–844.

Kumar, C., & Kumar, M. (2024). Session-based recommendations with sequential context using attention-driven LSTM. *Computers and Electrical Engineering*, *115*, 109138.

Lee, E. L., Kuo, T. T., & Lin, S. D. (2017). A collaborative filtering-based two stage model with item dependency for course recommendation. In: *Proceedings of 2017 IEEE International Conference on Data Science and Advanced Analytics*. Tokyo: IEEE, 496–503.

Levy, B., Hershkovitz, A., Tabach, M., Cohen, A., Segal, A., & Gal, K. (2023). Personalization in graphically rich e-learning environments for K-6 mathematics. *IEEE Transactions on Learning Technologies*, *16*(3), 364–376.

Li, Z. H., Wang, X. Z., Yang, C., Yao, L. N., McAuley, J., & Xu, G. D. (2023). Exploiting explicit and implicit item relationships for session-based recommendation. In: *Proceedings of the 16th ACM International Conference on Web Search and Data Mining*. Singapore: Association for Computing Machinery, 553–561.

Liang, G. H. (2025). Constructing Chinese online course learning system based on deep learning. *Procedia Computer Science*, *262*, 1424–1431.

Liang, D. W., Altosaar, J., Charlin, L., & Blei, D. M. (2016). Factorization meets the item embedding: Regularizing matrix factorization with item co-occurrence. In: *Proceedings of the 10th ACM Conference on Recommender Systems*. Boston: Association for Computing Machinery, 59–66.

Liang, C., Wu, Z. H., Huang, W. Y., & Giles, C. L. (2015). Measuring prerequisite relations among concepts. In: *Proceedings of the 2015 Conference on Empirical Methods in Natural Language Processing*. Lisbon: Association for Computational Linguistics, 1668–1674.

Lin, Y. G., Feng, S. B., Lin, F., Xiahou, J. B., & Zeng, W. H.

(2023). Multi-scale reinforced profile for personalized recommendation with deep neural networks in MOOCs. *Applied Soft Computing*, *148*, 110905.

Liu, Q., Zeng, Y. F., Mokhosi, R., & Zhang, H. B. (2018). STAMP: Short-term attention/memory priority model for session-based recommendation. In: *Proceedings of the 24th ACM SIGKDD International Conference on Knowledge Discovery & Data Mining*. London: Association for Computing Machinery, 1831–1839.

Ma, F. (2025). Learning behavior analysis and personalized recommendation system of online education platform based on machine learning. *Computers and Education: Artificial Intelligence*, *8*, 100408.

Nakagawa, H., Iwasawa, Y., & Matsuo, Y. (2019). Graph-based knowledge tracing: Modeling student proficiency using graph neural network. In: *Proceedings of IEEE/WIC/ACM International Conference on Web Intelligence*. Thessaloniki: Association for Computing Machinery, 156–163.

Pan, L. M., Li, C. J., Li, J. Z., & Tang, J. (2017). Prerequisite relation learning for concepts in MOOCs. In: *Proceedings of the 55th Annual Meeting of the Association for Computational Linguistics (Volume 1: Long Papers)*. Vancouver: Association for Computational Linguistics, 1447–1456.

Peters, B., Niculae, V., & Martins, A. F. T. (2019). Sparse sequence-to-sequence models. In: *Proceedings of the 57th Annual Meeting of the Association for Computational Linguistics*. Florence: Association for Computational Linguistics, 1504–1519.

Premalatha, M., Viswanathan, V., & Čepová, L. (2022). Application of semantic analysis and LSTM-GRU in developing a personalized course recommendation system. *Applied Sciences*, *12*(21), 10792.

Pu, J. H., Li, S. F., Guo, M., Chen, X., & Xiong, Z. (2024). Graph neural network based intelligent tutoring system: A survey. *Neurocomputing*, *610*, 128442.

Rahimi, A. R., & Ghorbani, B. D. (2025). Toward the language MOOC (LMOOC's) low dropout rate: The control-value theory of persistency in LMOOC (CVTPLMOOC). *Computers in Human Behavior Reports*, *17*, 100593.

Ren, J. R., & Wu, S. M. (2023). Prediction of user temporal interactions with online course platforms using deep learning algorithms. *Computers and Education: Artificial Intelligence*, *4*, 100133.

Rendle, S., Freudenthaler, C., Gantner, Z., & Schmidt-Thieme, L. (2009). BPR: Bayesian personalized ranking from implicit feedback. In: *Proceedings of the 25th Conference on Uncertainty in Artificial Intelligence*. Montreal: AUAI Press, 452–461.

Saraswat, M., & Srishti. (2022). Leveraging genre classification with RNN for book recommendation. *International Journal of Information Technology*, *14*(7), 3751–3756.

Sarwar, B., Karypis, G., Konstan, J., & Riedl, J. (2001). Item-based collaborative filtering recommendation algorithms. In: *Proceedings of the 10th International Conference on World Wide Web*. Hong Kong: Association for Computing Machinery, 285–295.

Shin, D., Shim, Y., Yu, H., Lee, S., Kim, B., & Choi, Y. (2021). SAINT+: Integrating temporal features for EdNet correctness prediction. In: *Proceedings of the 11th International Learning Analytics and Knowledge Conference*. Irvine: Association for Computing Machinery, 490–496.

Sun, F., Liu, J., Wu, J., Pei, C. H., Lin, X., Ou, W. W., & Jiang, P. (2019). BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformer. In: *Proceedings of the 28th ACM International Conference on Information and Knowledge Management*. Beijing: Association for Computing Machinery, 1441–1450.

Sun, J., Mei, S., Yuan, K., Jiang, Y., & Cao, J. (2024). Prerequisite-enhanced category-aware graph neural networks for course recommendation. *ACM Transactions on Knowledge Discovery from Data*, *18*(5), 1–21.

Tian, X. T., & Liu, F. (2021). Capacity tracing-enhanced course recommendation in MOOCs. *IEEE Transactions on Learning Technologies*, *14*(3), 313–321.

Volk, N. A., Rojas, G., & Vitali, M. V. (2020). UniNet: Next term course recommendation using deep learning. In: *Proceedings of 2020 International Conference on Advanced Computer Science and Information Systems*. Depok: IEEE, 377–380.

Wang, S. J., Cao, L. B., Wang, Y., Sheng, Q. Z., Orgun, M. A., & Lian, D. F. (2022a). A survey on session-based recommender systems. *ACM Computing Surveys (CSUR)*, *54*(7), 154.

Wang, S. J., Hu, L., Cao, L. B., Huang, X. S., Lian, D. F., & Liu, W. (2018). Attention-based transactional context embedding for next-item recommendation. In: *Proceedings of the 32nd AAAI Conference on Artificial Intelligence*. New Orleans: AAAI Press, 2532–2539.

Wang, Y. F., Ma, D. H., Ma, J. H., & Jin, Q. (2024a). HGCR: A heterogeneous graph-enhanced interactive course recommendation scheme for online learning. *IEEE Transactions on Learning Technologies*, *17*, 364–374.

Wang, M., Wang, M. J., Xu, X., Yang, L. Q., Cai, D. B., & Yin, M. H. (2024b). Unleashing ChatGPT's power: A case study on optimizing information retrieval in flipped classrooms via prompt engineering. *IEEE Transactions on Learning Technologies*, *17*, 629–641.

Wang, Z. Y., Wei, W., Cong, G., Li, X. L., Mao, X. L., & Qiu, M. H. (2020). Global context enhanced graph neural networks for session-based recommendation. In: *Proceedings of the 43rd International ACM SIGIR Conference on Research and Development in Information Retrieval*. Xi'an: Association for Computing Machinery, 169–178.

Wang, J. J., Xie, H. R., Wang, F. L., Lee, L. K., & Au, O. T. S. (2021). Top-N personalized recommendation with graph neural networks in MOOCs. *Computers and Education: Artificial Intelligence*, *2*, 100010.

Wang, M. J., Yu, H. Y., Bell, Z., & Chu, X. Y. (2022b). Constructing an Edu-Metaverse ecosystem: A new and innovative framework. *IEEE Transactions on Learning Technologies*, *15*(6), 685–696.

Wu, S., Tang, Y. Y., Zhu, Y. Q., Wang, L., Xie, X., & Tan, T. N. (2019). Session-based recommendation with graph neural networks. In: *Proceedings of the 33rd AAAI Conference on*

Artificial Intelligence. Honolulu: AAAI Press, 43.

Wu, S. Y., Wang, J., & Zhang, W. (2024). Contrastive personalized exercise recommendation with reinforcement learning. *IEEE Transactions on Learning Technologies*, *17*, 691−703.

Xiong, Z., Li, H. X., Liu, Z., Chen, Z. F., Zhou, H., Rong, W. G., & Ouyang, Y. X. (2024). A review of data mining in personalized education: Current trends and future prospects. *Frontiers of Digital Education*, *1*(1), 26−50.

Xu, C. F., Zhao, P. P., Liu, Y. C., Sheng, V. S., Xu, J. J., Zhuang, F. Z., Fang, J. H., & Zhou, X. F. (2019). Graph contextualized self-attention network for session-based recommendation. In: *Proceedings of the 28th International Joint Conference on Artificial Intelligence*. Macao: AAAI Press, 3940–3946.

Yu, J. F., Luo, G., Xiao, T., Zhong, Q. Y., Wang, Y. Q., Feng, W. Z., Luo, J. Y., Wang, C. Y., Hou, L., Li, Y. Z., & et al. (2020). MOOCCube: A large-scale data repository for NLP applications in MOOCs. In: *Proceedings of the 58th Annual Meeting of the Association for Computational Linguistics*. Association for Computational Linguistics, 3135–3142.

Zha, X., Dong, Y. M., Jiang, H. M., Xu, Z. H., & Wang, C. (2026). LLM-AGR: Large language model augmented graph representation learning for recommendation. *Knowledge-Based Systems*, *331*, 114791.

Zhang, J., Hao, B. W., Chen, B., Li, C. P., Chen, H., & Sun, J. M. (2019). Hierarchical reinforcement learning for course recommendation in MOOCs. In: *Proceedings of the 33rd AAAI Conference on Artificial Intelligence*. Honolulu: AAAI Press, 54.

Zhang, J. J., Ma, C. H., Mu, X. D., Zhao, P., Zhong, C. L., & Ruhan, A. (2021). Recurrent convolutional neural network for session-based recommendation. *Neurocomputing*, *437*, 157−167.

Zhang, L., Ma, M. X., Zhang, J. T., Xu, T., Han, D. J., Fan, L. K., & Zhao, Y. H. (2026). Meta-path sampling-enhanced course recommendation in heterogeneous networks. *Information Processing & Management*, *63*(3), 104482.

Zhao, Z. Y., Yang, Y. H., Li, C., & Nie, L. Q. (2020). Guessuneed: Recommending courses via neural attention network and course prerequisite relation embeddings. *ACM Transactions on Multimedia Computing, Communications, and Applications*, *16*(4), 132.

Zhou, L. Y., & Wang, Y. Y. (2025). Simulation of personalized English learning path recommendation system based on knowledge graph and deep reinforcement learning. *Scientific Reports*, *15*(1), 34554.