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Personalized Learning Resource Recommendation via Enhanced Graph Neural Networks

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Abstract: The intricate structure of knowledge points within learning resources and the diverse learning needs of users often lead to inconsistent recommendation outcomes. To mitigate this issue, this study introduces a personalized recommendation framework that integrates an improved graph neural network with user preference clustering. User behavior is examined from three dimensions-interaction patterns, self-directed learning awareness, and learning capability-to model individual learning preferences. A meta-data-driven representation of knowledge-point entities is incorporated into the graph neural network, enabling effective modeling of relationships among learning resources. After performing dual clustering on user preferences and resource entities, the framework identifies the correspondence between clusters to generate personalized recommendations. Experimental results show that the proposed approach achieves a precision of 60.96%, a recall of 65.42%, and an F-score of 62.57%, demonstrating its strong overall effectiveness.

Keywords: Enhanced graph neural network; user preference clustering; personalized learning resources; recommendation framework; dual-cluster modeling

1. Introduction

As educational informatization continues to deepen, online education has undergone rapid expansion, and the integration of digital technologies has created unprecedented development opportunities while shaping new directions for innovative learning models. Leveraging the powerful information transmission capabilities of the Internet, learners can now access a wider variety of learning resources, and learning activities are no longer confined to specific temporal or spatial settings. This flexibility not only enhances learner engagement but also increases the pedagogical value of high-quality resources, enabling more targeted and effective learning guidance. With the growing openness of online learning environments, premium resources are shared more widely and utilized more frequently [1], resulting in significantly heightened learner motivation and improved learning efficiency and outcomes [2].

Nevertheless, the sharp rise in the number of online learning users has accelerated the industrialization of learning resources. As these resources become increasingly commodified, the online education industry has experienced rapid and large-scale expansion. The resulting explosion of digital information has also introduced significant challenges in terms of resource organization, management, and effective utilization. In response to these issues, existing studies have begun to explore corresponding solutions [3]. for example, proposed a text classification model based on an enhanced graph neural network, constructing co-occurrence graphs of words and expanding relation matrices via key-phrase linking. By applying Markov chain sampling and multilevel dimensionality reduction, the model achieves large-scale text classification, though its accuracy remains suboptimal. As a core component of personalized learning systems, learning resource recommendation technologies aim to align resource characteristics with user needs, thereby facilitating the shift from traditional to personalized learning paradigms [4].

A deep learning-based personalized recommendation framework has been proposed for digital library resources, in which user characteristics and preference information are modeled to generate personalized recommendations [5]. Despite its effectiveness, the approach requires substantial user involvement in selecting target items, which limits its practical applicability.

Motivated by these challenges, this paper adopts a user-centered perspective [6] to develop a personalized learning resource recommendation method. By integrating user preference analysis with the structural features of learning resources and conducting extensive experimental validation and comparative testing, the proposed method demonstrates strong effectiveness and practical value.

2. Preference Mining Grounded in User Behavioral Characteristics

Understanding user characteristics is fundamental to identifying learners'foundational conditions and underlying preferences, which form the basis for setting personalized learning objectives and crafting tailored resource recommendation strategies, as emphasized by prior research on adaptive learning systems [7]. In modern e-learning environments, the significance of user characteristics is amplified by the diversity of learner profiles and behavior modalities, making it essential to analyze intrinsic learning factors before initiating resource matching processes [8].

To this end, our framework conducts a multidimensional analysis of online behavioral data to extract features related to individual preferences. These features include frequency of engagement, task completion patterns, and topic selection tendencies, which are indicative of learners'evolving goals and self-regulated learning behaviors [9].

Learning behavior in digital settings often follows goal-directed patterns, where users optimize their strategies-such as pacing, content sequencing, and media selection-to maximize efficiency and outcomes. These behavioral adaptations are not random; rather, they present identifiable, structured patterns that encode preference signals [10]. Recognizing and modeling such regularities are central to our approach.

As depicted in Figure 1, online learning systems-unlike traditional classroom environments reliant on teacher-student interaction-enable diversified learning experiences through real-time forums, multimedia-rich content, and asynchronous engagement opportunities. These platforms offer learners various modes of interaction such as posing questions, engaging in peer discussions, and participating in thematic dialogues, which collectively generate rich interactional data essential for mining individual preferences. In this framework, we capitalize on these data by structurally encoding them into a user-resource knowledge graph that underpins our recommendation strategy.

To achieve this, we draw directly from the methods proposed by Lyu et al. [11], who demonstrated the effectiveness of integrating structure-aware attention mechanisms with knowledge graph embeddings to improve both accuracy and explainability in recommendation systems. Their approach influenced two core aspects of our methodology. First, we embed user interaction patterns within a semantically enriched knowledge graph, thereby capturing the relational dynamics between users and learning content. Second, we incorporate a structure-aware attention module that dynamically adjusts the weight of different interaction paths based on their relevance, allowing the model to focus on the most informative behavioral cues. By applying this attention mechanism within the graph learning process, our framework effectively distills user intent and behavioral context, resulting in more precise and interpretable recommendations. This methodological design significantly enhances the ability to personalize learning paths, particularly in environments characterized by sparse or heterogeneous interaction data:

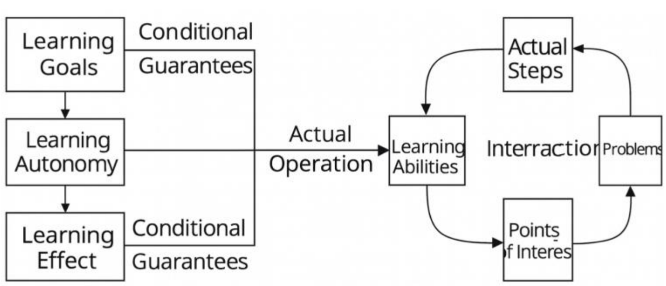

Figure 1. Preference Mining Method Based on User Characteristics

Learners'self-regulated learning awareness is another critical dimension. Throughout the learning process, users actively search for and browse knowledge aligned with their interests and learning needs [12]. The resulting behavioral traces-clicks, bookmarks, downloads-serve as direct or indirect reflections of user preferences. Meanwhile, asking questions, responding in knowledge communities, and offering feedback in forums also constitute meaningful expressions of learners'cognitive engagement and preference tendencies. Additionally, users often revisit and reinforce knowledge areas where they perceive deficiencies, and such repeated-learning behaviors are an integral component of resource recommendation models.

Moreover, users'mastery and comprehension levels determine the complexity of the learning resources appropriate for recommendation. As learners progress toward their academic goals, their knowledge depth typically improves through stages. Consequently, the degree to which users understand resource content fundamentally shapes the final recommendation outcomes.

Building on these considerations, this study identifies behavioral characteristics demonstrated during the learning process as key indicators for inferring user preferences, thereby supporting personalized learning resource recommendation.

3. Ontology Construction of Learning Resources Using an Enhanced Graph Neural Network

Effective recommendation of learning resources cannot rely solely on user preferences. In modern educational contexts, learning resources have become increasingly complex and diverse in both structure and form. Textual resources-such as course materials, case studies, indexes, online lectures, assignments, and examinations-represent only one portion of this expanding ecosystem. In response, this study develops a learning resource ontology built upon an improved graph neural network, using knowledge points as the foundational semantic units. This ontology captures the intrinsic principles governing the sharing and hierarchical organization of learning resources.

Unordered and unstructured learning resources must first be segmented and categorized. They can generally be classified into textual materials and media materials. While the former includes courseware, case documents, tests, and supplementary learning materials, the latter encompasses videos, animations, audio recordings, images, and multimodal content. For resources that cannot be easily assigned to predefined categories, the enhanced graph neural network is used to reorganize their relationships, leveraging a meta-data-based representation method to resolve ambiguity in knowledge-domain definitions.

The learning resource model constructed in this study is expressed as:

$$\gamma = \frac{\mathrm{sim}(x_1, x_2, \cdots, x_i)}{p}$$

In this model, γ denotes the constructed representation of a learning resource, x_i represents the knowledge-point components, and $\mathrm{sim}(x_1, x_2, \cdots, x_i)$ quantifies similarity among knowledge points. The parameter p represents the proportion of meta-data involved. The model supports knowledge-point management and retrieval by describing resource ontology structures based on these knowledge elements. Meta-data are further used to define hierarchical relationships across categories, such as textual types (materials, animations, instructional content) and media types (images, videos, audio, etc.) within the graph neural network.

The layered structure of the ontology captures differences in how knowledge is composed across learning resources. To articulate relationships among resources, the enhanced graph neural network incorporates four types of semantic links among knowledge points: parent, reference, dependency, and parallel. These relationships respectively capture whole-part hierarchy, citation-like connections, prerequisite or reliance patterns, and lateral independence among knowledge components.

4. A Resource Recommendation Algorithm Based on Dual Clustering of User Preferences and Resource Attributes

Once user preference data and learning resource ontology information have been obtained, this study applies a dual clustering mechanism to both elements to enhance the reliability of recommendation outcomes. Through this approach, independent clustering of users and learning resources is performed, and the final recommendations are produced by matching the resulting cluster structures.

Users grouped into the same cluster tend to exhibit highly similar preferences toward learning resources. To ensure maximum alignment between user needs and resource allocation within each cluster, the clustering criterion is defined according to users'evaluation results of learning resources. Let L denote the complete set of users and l_n the n clusters generated. The clustering structure is formalized as:

$$L = l_1 \cup l_2 \cup \cdots \cup l_n, \qquad l_i \cup l_j = \varnothing$$

Thus, n user clusters are generated, each associated with a defined cluster center. The evaluation results of the users located closest to the cluster center serve as representations of the cluster's learning objectives. The allowable distance between cluster members and the center is constrained to no more than 50%. The same clustering strategy is applied to learning resources.

Following the completion of both user and resource clustering, center similarity is computed to assess whether a given resource cluster satisfies the learning demands represented by the corresponding user cluster. The similarity function is defined as:

$$D = \mathrm{sim}(O_l, O_z)$$

where O_l and O_z denote the centers of the user and resource clusters, respectively. Based on this similarity measure, recommendation decisions are made using the criteria specified in Table 1.

Table 1: Resource Recommendation Decision Criteria

D Value	Decision Result
([0, 0.3))	Not recommended
([0.3, 0.5))	Further calculation of knowledge-point matching degree required
([0.5, 0.8))	Candidate recommendation; further calculation of knowledge-point matching degree required
([0.8, 1.0])	Recommended

According to the thresholds in Table 1, the algorithm determines whether a recommendation should be generated. For resources that require additional similarity calculations at the knowledge-point level, the same criteria in Table 1 are applied for the final decision.

5. Experiment and Evaluation

5.1 Experimental Setup

The experimental environment used in this study is Windows 10 (64-bit), equipped with an Intel® Core™ i5-3470 CPU and 64 GB of RAM. MATLAB R2020a was adopted as the development platform. To more rigorously validate the feasibility and effectiveness of the proposed algorithm, two perspectives-feasibility and performance-were considered during testing.

Ten students were randomly selected from an online education platform to participate in the experiment. All participants were university students, among whom four had excellent academic performance, three were average performers, and three were below average. Each student was assigned an identifier from 1 to 10 based on random ordering.

The experimental dataset was constructed using materials from the course Artificial Intelligence, comprising two categories: short-answer questions and objective test items. Details of the dataset are shown in Table 2.

Table 2: Experimental Data Configuration

Question Type	Quantity / items	Difficulty Level
Multiple-choice	210	Easy
	115	Medium
	45	Hard
Fill-in-the-blank	76	Easy

	46	Medium
	26	Hard
True/False	85	Easy
	42	Medium
	17	Hard
Short Answer	114	Easy
	62	Medium
	28	Hard

Using the data in Table 2 as the foundation, all question-answer data were normalized. The final score of subjective questions and the score of objective questions were mapped to the range $[0, 1]$. To ensure the reliability of evaluation, three metrics were established: Precision, Recall, and the F_1 -score, collectively used as the evaluation criteria of recommendation performance. Higher values of Precision, Recall, and F_1 indicate stronger performance.

The metrics are defined as:

$$P = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}}$$

$$R = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}}$$

$$F_1 = \frac{2R \times P}{R + P}.$$

In these formulas, P represents the degree of alignment between the recommended knowledge points and the learner's actual learning needs (i.e., recommendation accuracy); R represents the proportion of required knowledge points that are correctly recommended. TP, FP, and FN denote the number of correctly recommended knowledge points, incorrectly recommended knowledge points, and missing but necessary knowledge points, respectively.

5.2 Results and Analysis

To ensure the reliability of subsequent evaluation results, the contribution values of all knowledge points within the knowledge map were analyzed. The results are summarized in Table 3.

Table 3: Statistics of Knowledge Point Contribution Values

Knowledge Point	1	2	3	4	5	6	7
1	5.5						
2	5.5	1.5					
3	5.5		1.5				
4	6			1.5			
5	6		2		1.5		
6	6.5			2		1.5	
7	6.5			2			1.5

Building on this analysis, five students were randomly selected from the ten participants to evaluate the overall knowledge-point loss rate. The loss rates before learning the recommended content are shown in Table 4. After these five students completed the recommended learning tasks, the loss rates were recalculated, and the results are presented in Table 5.

Table 4: Statistics of Students'Knowledge-Point Loss Rates

Knowledge Point	Student ID 1	Student ID 3	Student ID 4	Student ID 6	Student ID 8
1	0.72	0.69	0.51	0.75	0.74
2	0.69	0.58	0.85	0.72	0.72
3	0.85	0.65	0.73	0.64	0.63
4	0.72	0.62	0.66	0.68	0.69
5	0.77	0.66	0.69	0.59	0.68
6	0.62	0.67	0.85	0.53	0.59
7	0.51	0.63	0.75	0.63	0.58

Table 5: Statistics of Students'Knowledge Point Loss Rates After Learning Recommended Content

Knowledge Point	Student No. 1	3	4	6	8
1	0.66	0.42	0.28	0.42	0.25
2	0.39	0.38	0.26	0.15	0.29
3	0.42	0.25	0.24	0.2	0.34
4	0.36	0.41	0.31	0.1	0.35
5	0.38	0.16	0.32	0.24	0.29
6	0.44	0.19	0.4	0.27	0.27
7	0.25	0.22	0.32	0.3	0.16

A comparison of Tables 4 and 5 reveals a substantial decline in knowledge-point loss rates following the use of the recommended content. This demonstrates that the proposed recommendation method effectively guides students toward knowledge areas crucial for their learning progression, thereby improving their comprehension and strengthening their diagnostic accuracy. Overall, the recommendation system achieves favorable results.

To further validate the superiority of the method, the SETB algorithm and the TBTFIDF algorithm were selected as baseline models. Experiments were conducted to compare the performance of all three methods. Through an analysis of the recommendation outcomes, the effectiveness of the proposed method was examined, and the final results are reported in Table 6.

Table 6: Recommendation Performance Statistics of Different Methods (%)

Metric	SETB	TBTFIDF	Proposed Method
P	22.96	24.36	60.96
R	26.38	29.44	65.42
F_1	19.44	20.83	62.57

As shown in Table 6, compared with SETB and TBTFIDF, the proposed method achieves higher recommendation precision, higher recall of recommended knowledge content, and a significantly improved F_1 score. This confirms that the method is capable of providing personalized learning-resource recommendations tailored to students'learning needs, thereby yielding notable improvements in learning outcomes.

6. Conclusion

With the continuous advancement of modern communication and information technologies, the global degree of resource sharing has significantly increased. While this trend greatly enriches the variety of learning resources available to learners, it also raises higher demands for effective resource selection. In particular, how to integrate the intrinsic knowledge structure of learning resources with learners'needs to achieve high-quality personalized recommendation has become an important question worthy of attention.

In this study, we investigate a personalized learning resource recommendation method that integrates an improved graph neural network with user preference clustering. Grounded in user behavioral data, the proposed method extracts user preferences and constructs a knowledge-point ontology for learning resources through an enhanced graph neural network. By leveraging clustering results for both users and resources, the algorithm identifies the optimal matching relationships and generates the final recommendation output.

Experimental evaluations show that the proposed method achieves promising performance. Through the designed approach, learners'utilization efficiency of learning resources is notably enhanced, and the time cost associated with resource selection is significantly reduced, thereby providing meaningful support for improving learning effectiveness.

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