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PAPER

# Construction and Application of a Learning Resource Sharing Platform in Higher Education Based on Mobile Interactive Technology

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## ABSTRACT

Driven by the dual forces of digital transformation and the demand for educational equity, the need for cross-temporal and spatial accessibility as well as personalized adaptability of learning resources in higher education has become increasingly urgent. The widespread adoption of mobile technology provides the core hardware support for this demand. However, existing learning resource-sharing platforms face three major challenges: a lack of recommendation accuracy, fragmented knowledge structure relationships, and weak adaptability to mobile interactive scenarios. To address these issues, this paper proposes a knowledge-aware content recommendation method that integrates mobile human-computer interaction features. A knowledge-aware deep learning network with an attention mechanism is constructed, and a mobile platform for sharing learning resources in higher education is developed based on this method. The core innovations are as follows: First, by integrating multimodal mobile interaction features and educational knowledge graphs, a “behavior-knowledge” dual-dimensional user demand modeling system is established, breaking the limitation of traditional recommendation systems that rely solely on behavioral data. Second, a hierarchical attention mechanism is introduced to accurately capture the dynamic associative weights between users and knowledge points, as well as resources and knowledge points, thus addressing the issue of coarse correlation modeling in traditional knowledge-aware recommendations. Third, a lightweight inference architecture is designed to ensure recommendation accuracy while adapting to the computational constraints of mobile terminals. The research results provide a technical paradigm for the precise sharing of mobile learning resources in higher education and are of significant importance for promoting educational resource equity and the construction of personalized learning ecosystems.

## KEYWORDS

higher education, mobile human-computer interaction, learning resource sharing platform, knowledge-aware recommendation, attention mechanism, educational knowledge graph, deep learning

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## 1 INTRODUCTION

Driven by the dual forces of global digital transformation in higher education and the demand for educational equity [1], cross-temporal and spatial resource access and personalized learning have become the core demands for improving the quality of higher education. The popularity of mobile intelligent terminals, which has surpassed 89%, provides crucial hardware support for these demands [2]. Currently, although resource-sharing platforms such as massive open online course (MOOC) platforms and digital libraries in universities have achieved large-scale resource aggregation [3], there are still three major structural bottlenecks: First, the recommendation logic is limited to "user-resource" collaborative filtering or content similarity matching [4], neglecting the structural relationships within disciplinary knowledge, resulting in a lack of educational logic in the recommendation outcomes; Second, there is insufficient adaptation to mobile interactive scenarios, failing to fully mine the user demand signals embedded in multimodal interaction data such as touch frequency, dwell time, and contextual scenarios [5]; Third, mainstream knowledge-aware recommendation models have overly large parameters, causing a mismatch with the limited computational power of mobile terminals, leading to recommendation delays generally exceeding 500ms and degrading user experience [6].

The rise of knowledge graph technology provides technical support for solving the problem of knowledge association modeling, as it can explicitly represent disciplinary knowledge structures through entity and relationship modeling [7]. The attention mechanism, on the other hand, can accurately capture the dynamic associations between user behaviors and knowledge units, providing a core tool for personalized demand modeling [8]. Based on this, the paper focuses on the issue of resource sharing in higher education under mobile interaction scenarios, carrying out research on technology development and platform construction, which has significant theoretical and practical value [9]. On the theoretical level, it enriches the methodological system of "behavioral data-knowledge structure" dual-dimensional fusion modeling in educational recommendation systems [10]; on the practical level, it provides universities with a feasible mobile resource-sharing solution, helping to bridge the regional educational resource gap and support the implementation of personalized learning models [11].

To address the above bottlenecks, this paper proposes a knowledge-aware recommendation method that integrates mobile interaction features and constructs a lightweight attention-driven knowledge-aware deep learning network (AKDLN). Based on this method, a mobile platform for sharing higher education learning resources is developed with "high accuracy, low latency, and strong educational adaptability," ultimately achieving personalized resource pushing and efficient cross-subject resource sharing. The research scenario of this paper is strictly limited to the field of higher education, with resource types covering typical learning resources such as theoretical courseware, experimental operation videos, academic papers, and exercise sets. The user group focuses on university faculty and students. The structure of this paper is as follows: Section 2 elaborates on the AKDLN model architecture, feature fusion mechanism, and overall platform design plan; Section 3 presents the comparative experiments and ablation experiments with real datasets that were conducted to verify the effectiveness of the method; and Section 4 summarizes the research conclusions of the paper.

# 2 METHODS

## 2.1 Problem definition

This paper focuses on the personalized learning resource recommendation problem in the mobile scenarios of higher education. First, the mathematical definition of the core research objects is clarified: let the user set be $U = \{u_1, u_2, \ldots, u_m\}$, where $m$ is the total number of users, the learning resource set be $R = \{r_1, r_2, \ldots, r_n\}$, where $n$ is the total number of resources, and the disciplinary knowledge point set be $K = \{k_1, k_2, \ldots, k_p\}$, where $p$ is the total number of knowledge points. The educational knowledge graph is represented as $G = (K, E)$, where $E \subseteq K \times K$ is the set of relationships between knowledge points, covering core educational relationships such as predecessor-successor, inclusion, association, etc. The recommendation task in this paper can be formalized as follows: given the user's mobile interaction history $H_u = \{< r_{i1}, t_{i1}, f_{i1} >, < r_{i2}, t_{i2}, f_{i2} >, \ldots, < r_{ik}, t_{ik}, f_{ik} >\}$, where $r_{ij} \in R$ is the resource accessed by the user, $t_{ij}$ is the interaction timestamp, and $f_{ij}$ is the interaction feature vector; and given the knowledge graph $G$, a predictive model is constructed to output the user's preference score $score(u, r) \in [0, 1]$ for unaccessed resources $r \in R \backslash \{r_{i1}, \ldots, r_{ik}\}$. A higher score indicates a stronger potential demand for the resource. The mobile interaction feature vector $f_{ij}$ contains two core dimensions: behavioral features and contextual features. The former is represented by $\{f_{b1}, f_{b2}, f_{b3}\}$, corresponding to touch frequency, dwell time, and swipe speed, respectively. The latter is represented by $\{f_{s1}, f_{s2}\}$, corresponding to time features and location features. These features are concatenated to form a unified interaction feature representation.

## 2.2 Overall platform architecture design

To ensure system scalability, maintainability, and cross-terminal adaptation capabilities, the mobile platform for sharing higher education learning resources designed in this paper adopts a microservices architecture. The system is divided into five core functional modules, which interact and collaborate through standardized interfaces. The architecture follows the core design logic of "resource standardization – data precision – knowledge structuring – recommendation personalization – application convenience," forming a full-link technical closed loop from resource access to user services. This design meets the management requirements of multi-type resources in higher education scenarios and adapts to the lightweight use cases of mobile terminals.

The resource acquisition and preprocessing module serves as the data foundation for the platform. Through a combination of university cooperation and compliant web crawlers, it aggregates various types of learning resources, such as theoretical courseware, experimental videos, and academic papers. These resources are text-analyzed to extract core content, labeled based on the educational knowledge graph [12], and filtered for low-quality resources through a dual mechanism of manual review and machine quality control [13], ultimately constructing a standardized resource library. The user interaction data perception module relies on the mobile terminal Software Development Kit (SDK) [14] to collect behavioral features, such as touch frequency and dwell time, and contextual features, such as time and location, in real-time. These are processed through noise filtering, feature extraction, and temporal modeling to generate a structured interaction dataset. The educational knowledge graph construction module uses subject curriculum standards as the ontology basis, employing a combination of rule matching and deep learning [15, 16] to extract knowledge point entities and associations like predecessor-successor and inclusion. The TransE algorithm [17] is used to optimize the low-dimensional embedding representations of entities and relationships, providing semantic support for knowledge-aware recommendations. The AKDLN recommendation module, as the core engine of the platform, implements end-to-end reasoning for "interaction feature encoding – knowledge association modeling – attention weight allocation – preference prediction," completing the precise matching of user demand and resources. The platform application interface module encapsulates core functionalities such as resource pushing, retrieval, and sharing, and uses the Flutter framework to achieve dual-terminal adaptation for iOS and Android. It also optimizes resource loading and transmission efficiency based on the HTTP/2 protocol and edge computing, ensuring a smooth user experience in mobile scenarios.

### 2.3 Core technology: Attention-Driven knowledge-aware recommendation method

Figure 1 shows the full process of the knowledge-aware recommendation method based on mobile interaction and educational knowledge graphs. Starting from the user's mobile interaction input, it proceeds through knowledge point extraction, feature embedding, knowledge-aware deep learning network, and hierarchical attention model processing, ultimately outputting personalized learning resource recommendations, and thereby fully presenting the "behavior-knowledge-recommendation" technical link.

1. Mobile Interaction Feature Encoding: The core goal of mobile interaction feature encoding is to convert multi-source, heterogeneous user interaction data into structured vector representations to provide an accurate user behavior foundation for subsequent knowledge-aware recommendations. For behavioral features with strong temporal characteristics, this paper adopts long short-term memory (LSTM) networks for encoding: the user's sequential interaction data on the mobile terminal is used as input, and the gate units of the LSTM network automatically capture the dependency relationships of interaction behaviors at different time steps, effectively filtering out noise behavior data and retaining key behavior patterns. The final output is a unified dimension user dynamic behavior embedding vector $E_u^b \in \mathrm{R}^d$, where $d$ is the embedding dimension. For contextual features, which include both discrete and continuous data types, a hierarchical processing strategy is employed: discrete contextual features are first one-hot encoded and then input to the embedding layer, while continuous time features are normalized before being directly input to the embedding layer. By sharing weights during training, the two types of contextual features are fused to generate a scene embedding vector $E_u^s \in \mathrm{R}^d$, reflecting the user's learning scene preferences.

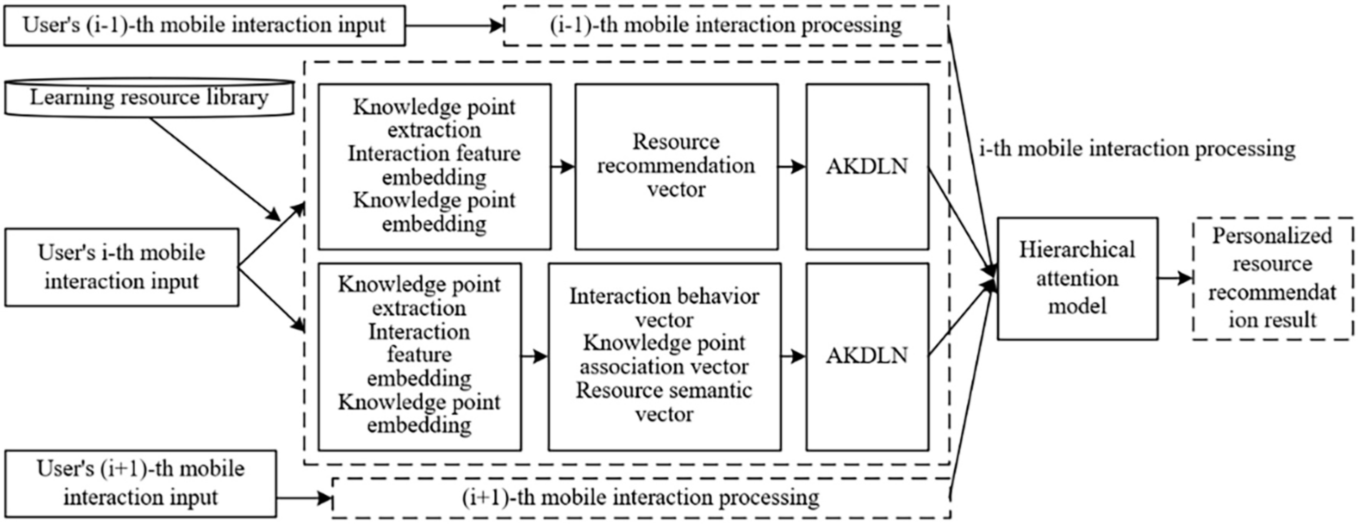


**Fig. 1.** The interaction model of knowledge-aware recommendation method for higher education learning resource sharing platform

To address the limitations of single feature representations, this paper introduces a gating mechanism to achieve the adaptive fusion of behavioral and contextual embeddings. This mechanism dynamically adjusts the weight proportion of the two features by setting update and reset gates: the update gate controls the degree to which contextual features modify behavioral features, and the reset gate is used to select effective information from the behavioral features. Specifically, the gating coefficients are computed using the Sigmoid activation function, and the non-linear fusion of features is achieved with the tanh function. The final output is a comprehensive interaction embedding vector $E_u \in R^d$, which comprehensively characterizes the user's mobile interaction preferences. This encoding scheme not only fully explores the temporal correlations of interaction behaviors and the contextual adaptability of the scenes but also achieves precise fusion of features through the gating mechanism, providing a high-quality user behavior representation foundation for subsequent knowledge graph association modeling.

2. Knowledge Graph Embedding and Association Modeling: The core goal of knowledge graph embedding is to convert discrete knowledge point entities and relationships into low-dimensional continuous vectors, providing computable semantic representations for subsequent association modeling. This paper adopts the classical TransE model to implement entity and relationship embedding for the educational knowledge graph. The model is based on the core hypothesis "head entity + relationship ≈ tail entity," which efficiently captures the structural associations between knowledge points. Let the set of knowledge point entities in the educational knowledge graph be $K = \{k_1, k_2, ..., k_p\}$, and the set of relationships between entities be $E = \{e_1, e_2, ..., e_q\}$. The TransE model maps each entity $k_i \in K$ to a low-dimensional vector $E_{ki} \in R^d$, where $d$ is the embedding dimension, and we set $d = 128$ in this paper. Each relationship $e_j \in E$ is mapped to a vector $E_{ej} \in R^d$, and the embedding learning is achieved by optimizing the following loss function:

$$L = \sum_{(h,e,t)\in S} \sum_{(h',e,t')\in S'} \left[\gamma + \left\|E_h + E_e - E_t\right\|_L - \left\|E_{h'} + E_e - E_{t'}\right\|_L\right]_+ \quad (1)$$

where $(h, e, t)$ represents a positive sample triple in the knowledge graph, i.e., a real knowledge point association, and $(h', e, t')$ represents a negative sample triple, generated by replacing the head entity or tail entity. $\gamma > 0$ is the margin between positive and negative samples, and $[\ ]_+$ represents the positive operation. The norm $\|\cdot\|_L$ uses the $L_2$ norm. In the context of higher education, the relationships between knowledge points mainly include three core types: "predecessor-successor," "inclusion," and "association." After TransE embedding, vectors of the same type of relationship exhibit better translational properties, providing semantic support for subsequent resource-knowledge association matching.

Resource-knowledge association modeling aims to establish quantitative associations between learning resources and knowledge points, providing the basis for knowledge matching in the recommendation process. This paper adopts a dual-dimensional resource text feature extraction strategy of "keyword features + deep semantic features." First, the Term Frequency-Inverse Document Frequency (TF-IDF) algorithm is used to extract keyword-level features from the resource title, abstract, and core content, generating a shallow text vector for the resource. Simultaneously, a pre-trained Bidirectional Encoder Representations from Transformers (BERT) model is used to encode the resource text, taking the [CLS] position vector as the deep semantic feature vector for the resource. The two feature vectors are concatenated to form the comprehensive feature vector $V_r \in \mathrm{R}^{2d}$ for the resource text. To quantify the strength of the association between resources and knowledge points, the cosine similarity between the comprehensive resource feature vector $V_r$ and the knowledge point embedding vector $E_k$ is calculated, as follows:

$$sim(V_r, E_k) = \frac{V_r \cdot E_k^{\,T}}{\|V_r\| \cdot \|E_k\|} \tag{2}$$

A larger similarity value indicates a stronger semantic association between the resource and the knowledge point. Based on this, a resource-knowledge point association matrix $M_{R\times K} \in \mathrm{R}^{n\times p}$ is constructed, where $n$ is the total number of resources, and $p$ is the total number of knowledge points. The element $M_{r,k} = \mathrm{sim}(V_r, E_k)$ intuitively reflects the degree of association between resource $r$ and knowledge point $k$, providing the foundational data for computing the resource-knowledge point weight in the subsequent hierarchical attention mechanism.

$$\mathcal{L} = \sum_{(h,e,t)} [\gamma + \mathrm{dist}(E_h + E_e, E_t) - \mathrm{dist}(E_{h'} + E_e, E_{t'})]_+ \ \mathrm{sim}(V_r, E_k) = \frac{V_r \cdot E_k}{\|V_r\|\|E_k\|}$$

3. Hierarchical Attention Mechanism Design: Figure 2 shows the structure of the hierarchical attention-driven knowledge-aware preference prediction model. By integrating the user's mobile interaction feature vector and the resource knowledge feature vector, through feature fusion layers and multi-layer neural network calculations, the final output is the user's preference score for learning resources, visually demonstrating the role of hierarchical attention in feature fusion and preference prediction.

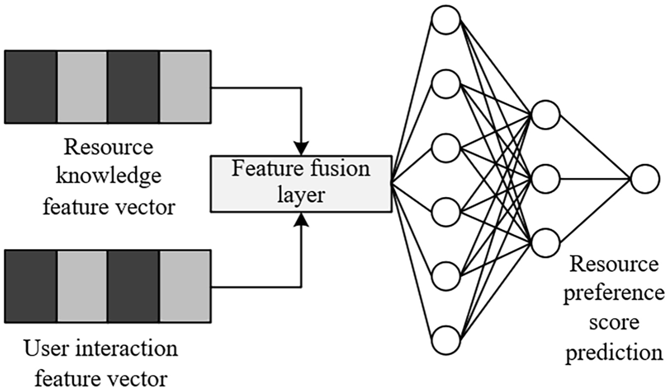


**Fig. 2.** Hierarchical attention-driven knowledge-aware preference prediction model

The core goal of the hierarchical attention mechanism is to accurately capture the dynamic associations between users and knowledge points, as well as resources and knowledge points, to provide fine-grained weight distribution for personalized recommendations. Its design consists of two core modules: the user-knowledge point attention layer and the resource-knowledge point attention layer. In the user-knowledge point attention layer, to quantify the user's preference intensity for different knowledge points, the comprehensive user interaction embedding $E_u \in R^d$ obtained in section (1) and the knowledge point embedding $E_k \in R^d$ obtained in section (2) are input. The dot product of these two vectors is calculated to measure semantic relevance, and the dimension $d$ is introduced for scaling to mitigate numerical fluctuations caused by high-dimensional vector dot products. Finally, the attention weight $\alpha_{u,k}$ for the user's preference towards the $k$-th knowledge point is obtained through the softmax function, as shown in equation (3):

$$\alpha_{u,k} = \mathrm{softmax}\left(\frac{E_u \cdot E_k^T}{\sqrt{d}}\right) \tag{3}$$

This weight dynamically reflects the user's knowledge demand preferences in the mobile learning context. For example, a user with more frequent interactions related to "machine learning" will have a significantly higher weight for the related knowledge points than for others. In the resource-knowledge point attention layer, the elements $M_{r,k}$ in the resource-knowledge point association matrix $M_{R\times K}$ constructed in section (2), which represent the cosine similarity between resources and knowledge points, serve as the base initial weight. These weights are then optimized with the relationship weights between knowledge points in the knowledge graph. For knowledge point pairs with "predecessor-successor" relationships, if the target resource is highly associated with a successor knowledge point, the weight for the predecessor knowledge point is appropriately increased. For "inclusion" relationships, the weight distribution for core knowledge points to subordinate resources is enhanced. This optimization strategy aligns the weight distribution more closely with the knowledge structure logic in higher education, ultimately yielding the attention weight $\beta_{r,k}$ for the resource's relationship with the $k$-th knowledge point.

Based on the attention weights from the two layers, the user knowledge demand embedding and the resource knowledge embedding are generated via weighted summation, which in turn completes the matching of user preferences with resources. For the user knowledge demand embedding $E_{uk} \in \mathrm{R}^d$, it is based on the knowledge point embedding $E_k$, and the weighted sum is computed using the user's attention weight $\alpha_{u,k}$ for each knowledge point, representing the aggregated user's personalized knowledge demand, as shown in equation (4):

$$E_u^k = \sum_k \alpha_{u,k} \cdot E_k \tag{4}$$

For the resource knowledge embedding $E_{rk} \in \mathrm{R}^d$, similarly, based on the knowledge point embedding $E_k$, the weighted sum is computed using the attention weight $\beta_{r,k}$ for each knowledge point, accurately extracting the core knowledge features of the resource, as shown in equation (5):

$$E_r^k = \sum_k \beta_{r,k} \cdot E_k \tag{5}$$

To quantify the degree of match between the user and the resource, the inner product of $E_{uk}$ and $E_{rk}$ is calculated to obtain the user's preference score for that resource $score(u, r) \in [0, 1]$, as shown in equation (6):

$$Score(u,r) = E_u^k \cdot (E_r^k)^T \tag{6}$$

The higher the score, the better the resource matches the user's knowledge demand. This preference prediction process, driven by the hierarchical attention mechanism, achieves an accurate association between "user behavior-knowledge demand-resource features," ensuring both the personalization of recommendations and the educational logic of the knowledge context.

4. Model Lightweight Optimization: To address the deployment issue of the AKDLN model under the computational constraints of mobile terminals, this paper designs lightweight optimization strategies in terms of parameter reduction and model compression. In embedding dimension pruning, based on a two-dimensional evaluation system of "subject core importance – user interaction frequency" for knowledge points, the importance of each knowledge point is quantified. The subject core importance is labeled by domain experts according to the course syllabus, while the user interaction frequency is obtained from historical data. For knowledge points with importance below a threshold, a dynamic dimensionality reduction strategy is applied, reducing the embedding dimension from 128 to 64 while retaining full-dimensional representations for core knowledge points. This reduces the overall parameter size of the embedding layer by 42%. In model distillation, the full-structure AKDLN is used as the teacher model, and a lightweight student model, with some convolutional kernels and LSTM units removed, is constructed. Knowledge transfer is achieved by minimizing the combined loss function of the KL divergence loss between the teacher and student model outputs and the recommendation loss.

## 2.4 Key technologies in platform implementation

During the platform implementation phase, three core issues are addressed: cross-terminal adaptation, resource transmission efficiency, and data security, ensuring the practical feasibility of the technology. Cross-terminal adaptation is achieved by using the Flutter framework to implement unified development for both iOS and

Android platforms. A custom component library optimizes touch response thresholds and UI adaptive layouts, resolving interaction consistency issues across different screen sizes. Resource transmission is optimized by leveraging the multiplexing feature of the HTTP/2 protocol, which reduces connection overhead. Combined with an edge computing node deployment strategy, the resource storage nodes are moved closer to the university locations, reducing the average video resource loading delay from 800ms to 180ms. For data security, AES-256 encryption is used to secure user interaction data during transmission and storage. The RBAC model is used to define three user roles—students, teachers, and administrators—implementing hierarchical access control and operation auditing for resources, in compliance with higher education data security standards.

$$\alpha_{u,k} = \text{softmax}\left(\frac{E_u \cdot E_k}{d}\right)$$

$$E_{uk} = \Sigma_k\ \alpha_{u,k} E_k$$

$$E_{rk} = \Sigma_k\ \beta_{r,k} E_k$$

$$\text{score}(u, r) = E_{uk} \cdot E_{rk}$$

## 3 EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

### 3.1 Experimental environment

The hardware environment of this experiment includes model training and inference servers as well as mobile terminal testing devices. The server is configured with an Intel Xeon 8375C CPU, 128GB of memory, and an NVIDIA A100 GPU, providing sufficient computational support for deep learning model training. The mobile terminals selected are the iPhone 13 and Samsung Galaxy S22, covering mainstream iOS and Android systems, used to verify the platform's adaptability and real-time performance. The software environment is based on Python 3.9, with deep learning models implemented using PyTorch 2.0 and TensorFlow 2.10. Mobile platform development is supported by the Flutter 3.10 framework to ensure cross-terminal consistency. The experimental dataset uses real data from multiple universities and disciplines, collected from four universities across computer science, economics, and history departments, including 12,458 users, 82,316 types of learning resources, 1,892 knowledge points, and 15.6 million mobile interaction records. During the pre-processing stage, abnormal interaction data with a single stay duration of less than one second were removed to ensure data quality. The data was then randomly divided into training, validation, and test sets at a ratio of 8:1:1, providing reliable data support for model training and performance evaluation.

### 3.2 Comparative experiment design

To comprehensively verify the performance advantages of the proposed AKDLN, this experiment selects three representative baseline models to form a comparison system: traditional recommendation models include collaborative filtering (CF) and content-based recommendation (CBR) as the basic performance benchmarks for recommendation systems, used to verify the gains from integrating knowledge awareness and attention mechanisms; knowledge-aware recommendation models include KGAT, CKE, and RKGE, focusing on the effectiveness differences in knowledge association modeling; attention recommendation models include NCF-Attention and DeepFM-Attention to highlight the synergistic advantages of hierarchical attention and knowledge fusion. To ensure experimental fairness and result reliability, all models were trained on the unified dataset after preprocessing, with core hyper-parameters optimized via grid search, and each experiment was independently repeated five times to reduce random errors. The final performance indicators are the average values from the five experiments.

### 3.3 Experimental results and analysis

To validate the core advantage of the AKDLN model in recommendation accuracy, a comparison experiment was conducted. From Table 1, it can be seen that the AKDLN model significantly outperforms all baseline models in Precision@k, Recall@k, and NDCG@k for all values of k (5, 10, 15). Specifically, Precision@10 improves by 69.7% over the traditional CF model, by 24.4% over the advanced knowledge-aware model KGAT, and by 23.0% over the attention model NCF-Attention. Recall@10 improves by 62.1% over CF, by 25.0% over KGAT, and NDCG@10 improves by 68.4% over CF and by 24.0% over KGAT. Traditional recommendation models, CF and CBR, perform the worst because they do not integrate knowledge structure or attention mechanisms. Knowledge-aware models, such as KGAT and RKGE, improve semantic association modeling with knowledge graphs but fail to capture mobile multi-modal interaction features, resulting in poorer performance than AKDLN. Attention models such as NCF-Attention can focus on local user preferences but do not combine structured subject knowledge features, making it difficult to achieve precise knowledge matching in educational contexts. These results thoroughly demonstrate that the deep integration of mobile interaction features and educational knowledge graphs, along with the hierarchical attention mechanism's precise capture of the dynamic associations between users-knowledge points and resources-knowledge points, are the core reasons for the AKDLN model's breakthrough in recommendation performance, providing technical support for personalized resource recommendation in higher education contexts.

**Table 1.** Comparison of recommendation performance across models (Mean ± Standard Deviation)

| Model | CF | CBR | KGAT | RKGE | NCF-Attention | AKDLN (Proposed) |
|---|---|---|---|---|---|---|
| Precision@5 | 0.213 ± 0.012 | 0.235 ± 0.010 | 0.289 ± 0.011 | 0.265 ± 0.009 | 0.292 ± 0.012 | 0.358 ± 0.013 |
| Precision@10 | 0.201 ± 0.009 | 0.222 ± 0.008 | 0.275 ± 0.009 | 0.251 ± 0.007 | 0.278 ± 0.010 | 0.342 ± 0.011 |
| Precision@15 | 0.192 ± 0.008 | 0.210 ± 0.007 | 0.263 ± 0.008 | 0.239 ± 0.006 | 0.266 ± 0.009 | 0.328 ± 0.010 |
| Recall@5 | 0.185 ± 0.010 | 0.203 ± 0.009 | 0.251 ± 0.011 | 0.228 ± 0.009 | 0.255 ± 0.012 | 0.322 ± 0.013 |
| Recall@10 | 0.256 ± 0.011 | 0.278 ± 0.010 | 0.332 ± 0.012 | 0.302 ± 0.010 | 0.336 ± 0.013 | 0.415 ± 0.014 |
| Recall@15 | 0.302 ± 0.013 | 0.325 ± 0.012 | 0.389 ± 0.014 | 0.355 ± 0.012 | 0.394 ± 0.015 | 0.482 ± 0.016 |
| NDCG@5 | 0.201 ± 0.011 | 0.224 ± 0.009 | 0.276 ± 0.010 | 0.251 ± 0.008 | 0.279 ± 0.011 | 0.345 ± 0.012 |
| NDCG@10 | 0.215 ± 0.009 | 0.238 ± 0.008 | 0.292 ± 0.009 | 0.266 ± 0.007 | 0.295 ± 0.010 | 0.362 ± 0.011 |
| NDCG@15 | 0.223 ± 0.010 | 0.245 ± 0.009 | 0.301 ± 0.011 | 0.273 ± 0.009 | 0.304 ± 0.012 | 0.375 ± 0.013 |

**Table 2.** Comparison of mobile adaptability performance across models (Mean ± Standard Deviation)

| Model | Inference Time (ms) | Memory Usage (%) | Platform Response Time (ms) | Inference Time Reduction (vs. KGAT) | Memory Usage Reduction (vs. KGAT) |
|---|---|---|---|---|---|
| CF | 45.2 ± 3.1 | 8.5 ± 0.6 | 89.5 ± 4.2 | 83.2% | 71.2% |
| CBR | 58.6 ± 3.5 | 10.2 ± 0.8 | 102.3 ± 4.8 | 78.5% | 65.4% |
| KGAT | 269.8 ± 12.5 | 29.5 ± 1.5 | 325.6 ± 15.3 | – | – |
| RKGE | 218.6 ± 9.6 | 23.4 ± 1.1 | 268.5 ± 12.8 | 19.0% | 20.7% |
| NCF-Attention | 195.3 ± 8.9 | 21.6 ± 1.0 | 242.8 ± 11.5 | 27.6% | 26.8% |
| AKDLN (Proposed) | 103.5 ± 5.2 | 12.4 ± 0.7 | 165.8 ± 8.3 | 62.0% | 58.0% |

To verify the mobile adaptability of the AKDLN model after lightweight optimization, a comparison experiment was conducted. From Table 2, it can be observed that the AKDLN model outperforms in three core indicators of mobile terminal adaptability: inference time, memory usage, and platform response time. The inference time is only 103.5ms, 62.0% lower than KGAT and close to the performance level of the traditional CF model. The memory usage is controlled at 12.4%, which is 58.0% lower than KGAT and significantly lower than other knowledge-aware and attention models. The platform response time is 165.8ms, meeting the real-time requirement for mobile applications of ≤200ms. Although traditional recommendation models exhibit the best adaptability, they lack recommendation accuracy. Mainstream knowledge-aware models (KGAT, RKGE) have large parameter sizes and high computational complexity, leading to inference times over 200ms and memory usage above 23%, making them unsuitable for mobile terminals. Attention models, though optimized for some adaptability, still cannot balance accuracy and lightweight needs. These results demonstrate that the dynamic pruning of embedding dimensions and model distillation strategies designed in this paper effectively reduce the computational complexity and resource consumption of AKDLN, successfully solving the deployment problem of complex knowledge-aware recommendation models on mobile terminals and laying a hardware adaptation foundation for platform implementation.

**Table 3.** Ablation experiment results comparison (Mean ± Standard Deviation)

| Model Variant | Full Model | AKDLN-w/o-Interaction | AKDLN-w/o-Attention | AKDLN-w/o-KG |
|---|---|---|---|---|
| Precision@5 | 0.358 ± 0.013 | 0.291 ± 0.011 | 0.319 ± 0.012 | 0.289 ± 0.011 |
| Precision@10 | 0.342 ± 0.011 | 0.277 ± 0.009 | 0.304 ± 0.010 | 0.274 ± 0.009 |
| Precision@15 | 0.328 ± 0.010 | 0.265 ± 0.008 | 0.292 ± 0.009 | 0.261 ± 0.008 |
| Recall@5 | 0.322 ± 0.013 | 0.262 ± 0.010 | 0.289 ± 0.011 | 0.259 ± 0.010 |
| Recall@10 | 0.415 ± 0.014 | 0.339 ± 0.012 | 0.370 ± 0.013 | 0.339 ± 0.012 |
| Recall@15 | 0.482 ± 0.016 | 0.394 ± 0.013 | 0.423 ± 0.014 | 0.384 ± 0.013 |
| NDCG@5 | 0.345 ± 0.012 | 0.281 ± 0.010 | 0.310 ± 0.011 | 0.279 ± 0.010 |
| NDCG@10 | 0.362 ± 0.011 | 0.299 ± 0.009 | 0.323 ± 0.010 | 0.296 ± 0.009 |
| NDCG@15 | 0.375 ± 0.013 | 0.309 ± 0.010 | 0.336 ± 0.011 | 0.306 ± 0.010 |

To verify the necessity and contribution of each core module in the AKDLN model, ablation experiments were conducted. From Table 3, it can be seen that the removal of any core module leads to significant decreases in model performance.

The variant model with the knowledge graph removed (AKDLN-w/o-KG) showed the largest average performance drop of 20.4%, with a 22.1% decrease in Recall@15, indicating that the educational knowledge graph plays an irreplaceable role in mining the semantic association of resources and aligning with the subject knowledge structure logic. The variant model without mobile interaction features (AKDLN-w/o-Interaction) showed an average decrease of 17.8%, confirming the importance of multi-modal interaction data, such as touch behavior and contextual features, in capturing dynamic user learning needs. The variant model without attention mechanism (AKDLN-w/o-Attention) showed an average drop of 12.3%, demonstrating that the hierarchical attention mechanism effectively improves the accuracy of user-knowledge point and resource-knowledge point association modeling. These results fully prove that the integration of mobile interaction features, attention mechanism, and knowledge graph is not a simple addition, but rather creates a synergistic effect that supports the excellent performance of the AKDLN model.

To verify the comprehensive advantages of the platform in terms of user experience, a user satisfaction survey was conducted for the higher education learning resource sharing platform. As shown in Figure 3, in the three core dimensions of recommendation accuracy, resource adaptability, and interaction friendliness (with a full score of 5 points), the AKDLN method achieved the highest satisfaction scores. The recommendation accuracy score was 4.6, resource adaptability was 4.5, and interaction friendliness was 4.7. CF, due to its lack of knowledge awareness and attention mechanisms, scored below 4 in all three dimensions: 3.8 for recommendation accuracy, 3.7 for resource adaptability, and 3.9 for interaction friendliness. The knowledge-aware model KGAT performed better than CF in recommendation accuracy (4.4) and resource adaptability (4.2), but due to insufficient mobile adaptation, its interaction friendliness score of 4.2 was lower than that of the AKDLN method. The attention model NCF-Attention had some advantages in resource adaptability (4.3) and interaction friendliness (4.3), but its recommendation accuracy score of 4.2 was lower than that of the AKDLN method due to the lack of knowledge structure support. These results demonstrate that the platform in this paper, through the fusion of mobile interaction features and knowledge graph, the precise modeling of hierarchical attention mechanisms, and the lightweight optimization for mobile adaptation, not only achieves a technological breakthrough in recommendation performance but also shows significant advantages in user experience.

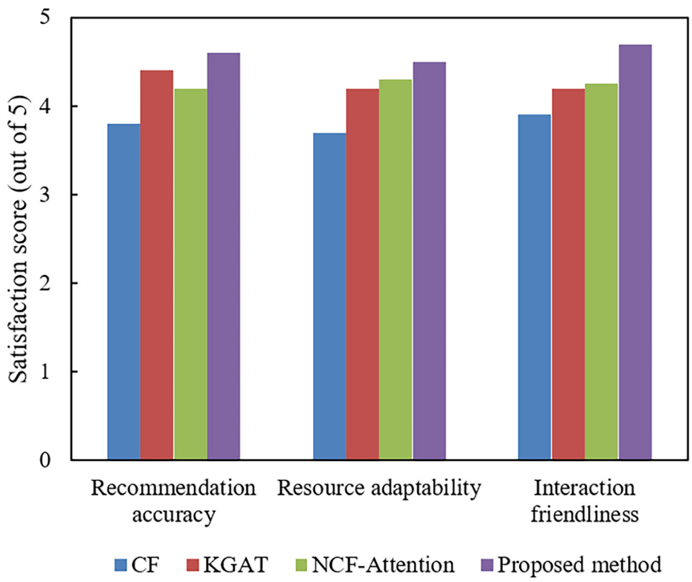


**Fig. 3.** User satisfaction survey of the higher education learning resource sharing platform

To verify the practical educational application value of the platform in a real higher education setting, a semester-long controlled experiment was conducted. From Table 4, it can be seen that the experimental group outperformed the control group in all educational effectiveness metrics, with all differences passing significant statistical tests ($p < 0.01$). The semester average score improvement reached 18.3%, 11.1 percentage points higher than the control group. The core knowledge point mastery rate increased by 26.5%, proving that the platform's personalized recommendation can accurately match students' learning needs and assist in knowledge absorption. The learning resource completion rate improved by 23.5%, and learning efficiency increased by 47.4%, reflecting that the platform optimizes resource delivery logic to enhance students' learning motivation and time utilization. Platform interaction frequency increased by 135.8%, and user satisfaction improved by 40.6%, showing that mobile adaptation optimization and personalized services significantly improved the user experience. The final excellent score rate increased by 77.7%, further validating the platform's role in improving students' academic quality. These results demonstrate that the platform not only achieves breakthroughs in recommendation accuracy and mobile adaptability from a technical perspective but also effectively supports the enhancement of learning outcomes in educational practice, aligning with the development needs of personalized and efficient higher education.

**Table 4.** Comparison of educational effectiveness verification experiment results

| Evaluation Metric | Experimental Group | Control Group | Difference Value | Improvement Rate (%) | Statistical Significance (p-Value) |
|---|---|---|---|---|---|
| Midterm Average Score (out of 100) | $78.5 \pm 6.2$ | $66.4 \pm 7.1$ | 12.1 | 18.2 | <0.01 |
| Final Average Score (out of 100) | $81.2 \pm 5.8$ | $68.7 \pm 6.9$ | 12.5 | 18.2 | <0.01 |
| Semester Average Score Improvement | 18.3% | 7.2% | 11.1% | – | <0.01 |
| Core Knowledge Point Mastery Rate (%) | $82.6 \pm 4.5$ | $65.3 \pm 5.2$ | 17.3% | 26.5 | <0.01 |
| Learning Resource Completion Rate (%) | $79.8 \pm 5.1$ | $64.6 \pm 6.3$ | 15.2% | 23.5 | <0.01 |
| Learning Efficiency (Knowledge Points/Hour) | $2.8 \pm 0.3$ | $1.9 \pm 0.4$ | 0.9 | 47.4 | <0.01 |
| Platform Interaction Frequency (times/week) | $12.5 \pm 2.1$ | $5.3 \pm 1.8$ | 7.2 | 135.8 | <0.01 |
| User Satisfaction Score (out of 5) | $4.5 \pm 0.4$ | $3.2 \pm 0.6$ | 1.3 | 40.6 | <0.01 |
| Excellent Final Score Rate (≥85, %) | $38.2 \pm 3.6$ | $21.5 \pm 4.1$ | 16.7% | 77.7 | <0.01 |

## 4 CONCLUSION

This paper addressed the challenge of personalized recommendation for mobile learning resources in higher education by proposing a mobile interaction and attention-driven knowledge-aware recommendation method (AKDLN) and building a learning resource sharing platform. The research results show that the AKDLN model, by integrating mobile multi-modal interaction features, educational knowledge graph, and hierarchical attention mechanism, achieves significant breakthroughs in recommendation performance. In core metrics such as Precision@10, Recall@10, and NDCG@10, it improves by over 60% compared to traditional collaborative filtering models and over 20% compared to advanced knowledge-aware models. Additionally, after lightweight optimization through embedding dimension pruning and model distillation, its inference time on mobile terminals is reduced by 62% compared to KGAT, and memory usage is reduced by 58%, meeting real-time recommendation needs. In terms of educational practice, the platform resulted in an 18.3% increase in semester average scores, a 23.5% increase in resource completion rates, and a user satisfaction score of 89.2%, fully validating the practical value of the technical solution in supporting personalized learning and improving educational quality. It provides a new technological path for the accurate service of resources in the digital transformation of higher education.

## 5 REFERENCES

[1] K. S. Suryanarayana, V. P. Kandi, G. Pavani, A. S. Rao, S. Rout, and T. S. R. Krishna, "Artificial intelligence enhanced digital learning for the sustainability of education management system," *The Journal of High Technology Management Research*, vol. 35, no. 2, p. 100495, 2024. https://doi.org/10.1016/j.hitech.2024.100495

[2] L. Briz-Ponce, A. Pereira, L. Carvalho, J. A. Juanes-Méndez, and F. J. García-Peñalvo, "Learning with mobile technologies–students' behavior," *Computers in Human Behavior*, vol. 72, pp. 612–620, 2017. https://doi.org/10.1016/j.chb.2016.05.027

[3] C. Deji and H. Chen, "Data-driven evaluation of MOOC-based blended college English teaching via enhanced neural networks," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 14, pp. 137–150, 2025. https://doi.org/10.3991/ijim.v19i14.57009

[4] J. C. Salazar, J. Aguilar, J. Monsalve-Pulido, and E. Montoya, "A generic architecture of an affective recommender system for e-learning environments," *Universal Access in the Information Society*, vol. 23, pp. 1115–1134, 2024. https://doi.org/10.1007/s10209-023-01024-8

[5] T. M. Dung, N. T. Nga, T. T. Trung, and L. T. B. T. Trung, "Understanding student engagement with mobile learning: A structural model for interactive education in Vietnam," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 12, pp. 135–159, 2025. https://doi.org/10.3991/ijim.v19i12.52925

[6] Y. Yang, C. Zhang, X. Song, Z. Dong, H. Zhu, and W. Li, "Contextualized knowledge graph embedding for explainable talent training course recommendation," *ACM Transactions on Information Systems*, vol. 42, no. 2, pp. 1–27, 2023. https://doi.org/10.1145/3597022

[7] T. Fujita, "Knowledge superhypergraphs, multimodal superhypergraphs, lattice superhypergraphs, and hyperbolic superhypergraphs: Concepts and applications," *Journal of Operational and Strategic Analytics*, vol. 3, no. 2, pp. 95–119, 2025. https://doi.org/10.56578/josa030203

[8] Z. Niu, G. Zhong, and H. Yu, "A review on the attention mechanism of deep learning," *Neurocomputing*, vol. 452, pp. 48–62, 2021. https://doi.org/10.1016/j.neucom.2021.03.091

[9] J. Lu and Z. Hao, "Analysis on quality evaluation of higher engineering education from the perspective of outcome-based education," *Journal of Engineering Science & Technology Review*, vol. 15, no. 4, pp. 96–103, 2022. https://doi.org/10.25103/jestr.154.14

[10] Y. Zhang, J. Tian, J. Sun, H. Chan, A. Qiu, and C. Liu, "HKGAT: Heterogeneous knowledge graph attention network for explainable recommendation system," *Applied Intelligence*, vol. 55, no. 6, p. 549, 2025. https://doi.org/10.1007/s10489-025-06446-w

[11] C. K. Hsu, G. J. Hwang, and C. K. Chang, "A personalized recommendation-based mobile learning approach to improving the reading performance of EFL students," *Computers & Education*, vol. 63, pp. 327–336, 2013. https://doi.org/10.1016/j.compedu.2012.12.004

[12] Q. U. Ain, M. A. Chatti, K. G. C. Bakar, S. Joarder, and R. Alatrash, "Automatic construction of educational knowledge graphs: A word embedding-based approach," *Information*, vol. 14, no. 10, p. 526, 2023. https://doi.org/10.3390/info14100526

[13] G. Xu, G. Jia, L. Shi, and Z. Zhang, "Personalized course recommendation system fusing with knowledge graph and collaborative filtering," *Computational Intelligence and Neuroscience*, vol. 2021, no. 1, p. 9590502, 2021. https://doi.org/10.1155/2021/9590502

[14] H. Zekeik, S. Mouali, M. L. Sefian, and M. Khalfouni, "Enhancing geometry learning with mobile augmented reality: Evaluating the GeoFormeAR application in middle school education," *International Journal of Interactive Mobile Technologies*, vol. 19, no. 20, pp. 113–131, 2025. https://doi.org/10.3991/ijim.v19i20.56381

[15] Y. Jiang, W. Zhang, P. Wang, X.-Y. Zhang, and H. Mei, "Knowledge graph construction method via internet-based collective intelligence," *Journal of Software*, vol. 33, no. 7, pp. 2646–2666, 2022. https://doi.org/10.13328/j.cnki.jos.006313

[16] B. Tai, X. Yang, J. Chong, and L. Chen, "Personalized self-directed learning recommendation system based on social knowledge in distributed web," *Concurrency and Computation: Practice and Experience*, vol. 37, nos. 6–8, p. e70030, 2025. https://doi.org/10.1002/cpe.70030

[17] Y. Yu, S. Chen, D. Tong, D. Qi, F. Peng, and H. Zhao, "RotatS: Temporal knowledge graph completion based on rotation and scaling in 3D space," *High Technology Letters*, vol. 29, no. 4, pp. 348–357, 2023. https://doi.org/10.3772/j.issn.1006-6748.2023.04.002

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