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PAPER

A Personalized Recommendation Framework for Online Legal Education Integrating Context Awareness and Mobile Interaction

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ABSTRACT

Significant limitations in existing personalized recommendation systems for online legal education include the neglect of contextual heterogeneity, lack of affective association, the fragmentation of interaction feedback loops, and insufficient domain-specific sentiment-labeled data. To address these issues, a collaborative recommendation framework integrating transfer learning, a sentiment-enhanced knowledge graph (SE-KG), and a knowledge graph convolutional network (KGCN) was proposed. Methodologically, a richly annotated general-domain film review corpus was employed as the source domain, through which transfer learning was applied to optimize a long short-term memory (LSTM) network, quantifying and accurately annotating sentiment tendencies in textual evaluations of legal education resources. A core knowledge graph (KG) encompassing "knowledge points – legal provisions – cases – courseware" was then constructed, into which the quantified sentiment outputs were embedded to generate the SE-KG, with additional relational triplets such as "sentiment similarity" and "user–preference sentiment" incorporated. Finally, context-aware data and mobile interaction sequences were fused, and the KGCN's neighbor aggregation mechanism was refined with an attention strategy to enable dynamic user preference prediction. Experiments show that the framework mitigates the shortage of sentiment-labeled legal data and significantly improves recommendation accuracy, recall, and users' mastery of knowledge points compared with traditional collaborative filtering and baseline KGCN models. This work offers a new approach for personalized resource delivery in online legal education through cross-domain sentiment transfer and KG enhancement, significantly improving contextual adaptability and semantic relevance in recommendation systems.

KEYWORDS

context awareness, mobile interactive learning, online legal education, personalized recommendation, sentiment computing, knowledge graph convolutional network (KGCN), transfer learning

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1 INTRODUCTION

The deep integration of digital technologies with the education sector [1, 2] has accelerated the transition of online legal education toward mobile and personalized modes of delivery [3]. The convenience of mobile learning has rendered it a primary modality for law students preparing for professional qualification examinations, as well as for in-service legal practitioners seeking to update their knowledge structures [4, 5]. Consequently, personalized resource recommendation has become a fundamental requirement for enhancing learning efficiency [6, 7]. Despite this trend, existing recommendation systems for online legal education continue to encounter several core limitations. First, the strong semantic interdependencies inherent in legal knowledge and the sentiment orientations embedded within legal education resources are frequently overlooked. Critical information—such as the contentious nature of legal cases and user sentiment responses to the contextual application of legal provisions—has not been effectively captured, resulting in recommendations that lack deep semantic alignment [8, 9]. Second, insufficient context adaptability persists, as current systems fail to account for fragmented learning schedules, multi-device switching scenarios, and heterogeneous learning objectives, thereby limiting the capacity to accommodate the dynamic characteristics of mobile learning [10–12]. Third, the scarcity of sentiment-labeled data within the legal domain presents a significant bottleneck: the annotation of sentiment features in legal education resources is costly, and the limited availability of labeled samples constrains the implementation of sentiment-driven recommendation mechanisms [13, 14]. Fourth, the absence of a closed-loop design between interaction feedback and recommendation models remains a critical limitation. Interaction data generated through mobile engagement—such as browsing duration, error tagging, and discussion participation—have not been systematically incorporated, inhibiting the dynamic adaptation of recommendation strategies to evolving user learning states [15–17].

Against this backdrop, transfer learning provides a new pathway for mitigating the lack of sentiment-labeled data in specialized domains. By adapting sentiment knowledge from general-purpose textual corpora to legal education content, domain-specific sentiment quantification can be achieved. In parallel, the SE-KG development enriches the semantic relational structure of legal knowledge. When combined with the capacity of KGCNs to capture higher-order relational dependencies, these advancements offer a feasible technical route for addressing the current limitations of recommendation systems in online legal education.

The central objective of this study is to design and validate a personalized recommendation framework for legal education that integrates context awareness, mobile interaction, SE-KG, and advanced deep learning techniques. To accomplish this objective, three core research questions need to be addressed: (a) how transfer learning can be employed to optimize the LSTM network so that sentiment tendencies in legal education resources can be quantified and annotated with precision and efficiency using general-purpose sentiment-labeled datasets; (b) how a domain-specific KG for legal education can be constructed, and how sentiment quantification results can be transformed into semantically meaningful relational triplets—such as "sentiment similarity" and "user–preference sentiment"—to generate a SE-KG capable of strengthening recommendation support; and (c) how context-aware data, mobile interaction sequences, and the SE-KG can be jointly integrated into the KGCN, and how the neighbor aggregation mechanism of the model can be optimized to enhance the accuracy of user preference prediction.

To provide a clear structure for the study, the subsequent sections are organized below. Section 2 presents the core methodologies related to data modeling in the legal education domain, the LSTM-based transfer learning approach for sentiment prediction, the construction of the SE-KG, and the context–sentiment fusion KGCN model. Section 3 details the overall system architecture and implementation of the key modules. Section 4 reports the results of comparative experiments conducted to evaluate recommendation performance and user experience. The final section summarizes the main contributions and findings of the study.

2 METHODOLOGIES

2.1 Data modeling in the legal education domain

Data modeling constitutes the foundational prerequisite for constructing a personalized recommendation system, as its quality directly influences the performance of subsequent sentiment computing, KG construction, and the preference prediction model. The professional and multi-dimensional characteristics of data in the legal education domain impose heightened requirements on the specificity and structured organization of the modeling process. Four categories of core data were defined. Legal education resource data comprise essential learning materials, including legal provisions, representative cases, instructional courseware, and specialized practice items. User data encompass learner profiles, differentiated learning objectives, and stratified cognitive levels. Context-aware data capture the degree of temporal fragmentation during mobile learning, the types of terminal devices used, and specific learning scenarios. Interaction data incorporate real-time behavioral feedback collected from mobile platforms, including browsing duration, error tagging, case discussion participation, and resource ratings. Based on these data categories, targeted preprocessing procedures were implemented. Resource texts were structured through tokenization and case-cause classification. Learner profiles were mapped through quantitative scoring methods. Context-aware data were standardized to eliminate differences in magnitude. Interaction data were modeled in temporal sequence to preserve behavioral dependency patterns. Through these processes, a normalized and high-quality dataset was ultimately formed.

2.2 LSTM-based transfer learning model for sentiment tendency prediction

The quantification of sentiment tendencies serves as a fundamental prerequisite for constructing the SE-KG. However, the scarcity and high annotation cost of sentiment-labeled data in the legal education domain hinder the direct training of a domain-specific sentiment prediction model with satisfactory accuracy. To address this constraint, transfer learning was introduced as a key strategy for enabling cross-domain adaptation of sentiment models. In this framework, an openly available film review dataset—characterized by rich sentiment annotations and diverse sentiment expressions—was adopted as the source domain D_s, while legal education resource texts constitute the target domain D_t. Domain adaptation techniques were employed to reduce the distributional discrepancy between the two domains. The core mechanism involves introducing a domain-adversarial loss function $L_{adv} = -E_{xs\sim Ds}\log D(x_s) - E_{xt\sim Dt}\log(1-D(x_t))$, where D denotes the domain discriminator, and x_s and x_t represent samples drawn from the source and target domains, respectively. Minimization of this loss enables effective transfer of sentiment features. The underlying principle lies in leveraging the general sentiment expression patterns learned from the source domain and transferring them to the target domain, where they are adapted to the specialized linguistic structures of legal texts, thereby substantially mitigating the limitations imposed by insufficient labeled samples in the target domain.

A four-stage progressive architecture was adopted. In the input layer, preprocessed text is transformed into low-dimensional dense word embedding vectors using either Word to Vector (Word2Vec) or Global Vectors for Word Representation (GloVe), ensuring effective representation of semantic information. The LSTM layer then captures sequential emotional dependencies through its gated mechanisms, mitigating the gradient vanishing problem in long text sequences. In this layer, the hidden state dimension is set to 256, and a dropout rate of 0.5 is applied to prevent overfitting. The fully connected layer functions as the core module for domain adaptation. The domain-adaptive loss function is embedded into this layer to minimize distributional discrepancies between the source and target domains, thereby enabling feature-level domain transfer. This layer also outputs multi-dimensional sentiment probabilities. In the output layer, sentiment categories are refined to reflect the characteristics of educational scenarios: instead of the conventional positive/neutral/negative triad, four domain-specific sentiment labels—"easy to understand," "inspirational," "highly practical," and "tedious"—are defined. The posterior probability of each sentiment category is generated as the final output. For sentiment quantification, a sigmoid function was employed to map the predicted sentiment probabilities into the interval [0,1], yielding sentiment scores S_k for each category. A subset of 1,000 legal education resource texts was manually annotated. The mean squared error (MSE) between the quantified score and the manually annotated ground-truth score $\hat{S}_{i,k}$ is computed as:

$$L_{MSE} = \frac{1}{1000}\sum_{i=1}^{1000}\sum_{k=1}^{4}(S_{i,k} - \hat{S}_{i,k})^2 \tag{1}$$

Iterative optimization of model parameters was subsequently performed to improve quantification precision and ensure the reliability of the resulting sentiment annotations.

2.3 Construction of the SE-KG for legal education

Conventional KGs for legal education primarily focus on semantic relationships among knowledge points, legal provisions, and cases, yet rarely incorporate sentiment dimensions. This limitation constrains the ability of such graphs to support sentiment-driven personalized recommendation. The objective of the SE-KG is therefore to integrate the sentiment quantification results obtained in Section 2.2 with the domain KG, thereby enriching the semantic relational structure. The construction process began with the development of the original legal education KG. Four core node types—knowledge point, legal provision, case, and courseware—were defined, accompanied by three foundational semantic relations: contains, associated with, and applicable to. The Neo4j graph database was employed for graph storage and management due to its capacity for efficient node relationship querying and graph traversal, making it well suited to the complex relational characteristics of legal domain knowledge. Building on this structure, three categories of sentiment-enhanced triplets were designed to expand the semantic dimensions of the graph: (a) Resource A – sentiment similarity – Resource B, which links educational resources exhibiting comparable sentiment orientations; (b) Resource A – sentiment complementarity – Resource B, which connects resources with complementary sentiment profiles; (c) User U – preference sentiment – Resource R, which represents the relationship between a user and the sentiment attributes of a resource. Each triplet was constructed in strict accordance with KG representation standards to ensure semantic consistency.

To maintain the dynamic adaptability of the SE-KG, an incremental update mechanism was introduced. Based on the sentiment prediction results of newly uploaded legal education resources, new sentiment-associated triplets were automatically generated and incorporated into the graph. An initial weighting formula was applied as follows:

$$w_0 = \frac{1}{K} \tag{2}$$

where, w_0 denotes the initial weight assigned to newly generated sentiment relations, and K represents the number of sentiment-neighbor nodes of the same type associated with the target resource. After the initialization of weights, sentiment relation weights were dynamically updated by incorporating interaction feedback obtained from users' mobile devices. The update process was implemented through the weighted iterative formula $w_{t+1} = \alpha w_t + (1-\alpha)f(r_u)$, where w_{t+1} is the updated sentiment relation weight, w_t is the historical weight, $\alpha = 0.7$ is the smoothing coefficient, and $f(r_u)$ denotes the mapping function applied to user feedback. $f(r_u)$ was implemented using a standardization process:

$$f(r_u) = \frac{r_u - \min_r}{\max_r - \min_r} \tag{3}$$

where, r_u is the raw user feedback value, and $\min_r = 1$ and $\max_r = 5$ correspond to a five-point rating scale. The mapped quantitative values were constrained within the range [0,1]. Through this mechanism, the SE-KG is able to continuously reflect changes in resource sentiment attributes and evolving user preferences, providing sentiment-rich, semantically knowledge support for the subsequent KGCN-based user preference prediction. Figure 1 illustrates the structure of the SE-KG, demonstrating the hierarchical relationships among knowledge nodes, resource nodes, context nodes, and sentiment nodes, as well as the integrated semantic, contextual, and sentiment-level relational structures.

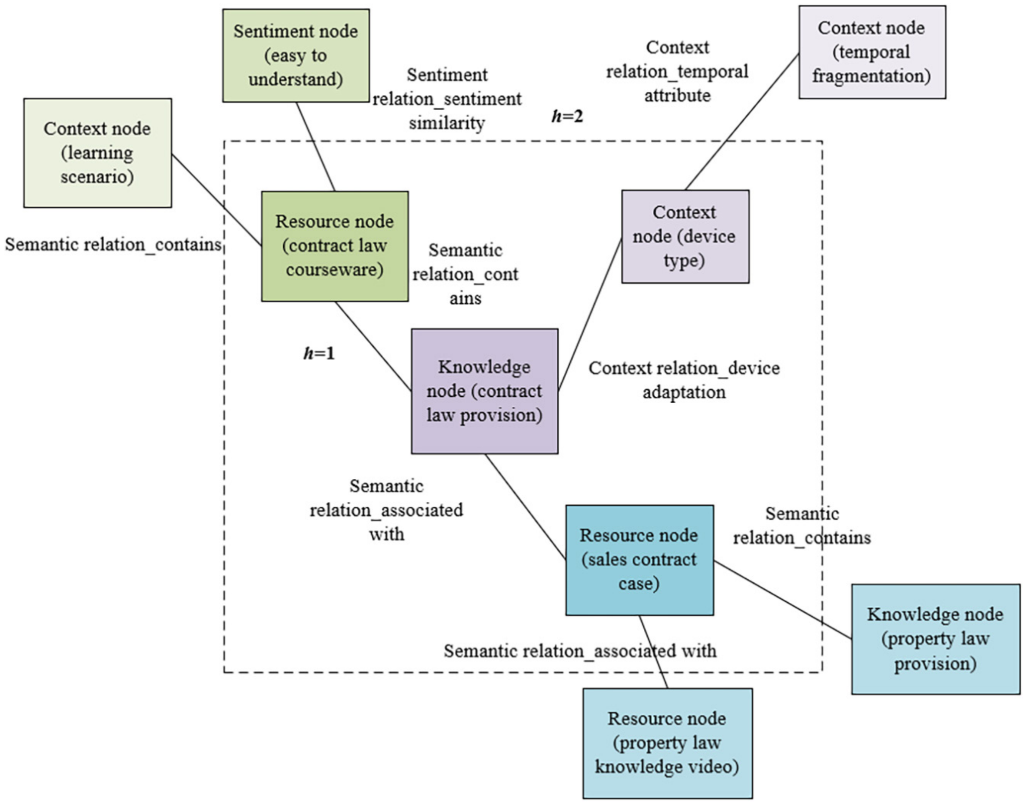

Fig. 1. Schematic representation of the SE-KG for legal education

2.4 Context-aware and interaction data modeling

Contextual variability and real-time interaction feedback serve as essential foundations for personalized recommendations in mobile learning environments. Their accurate modeling directly determines the dynamic adaptability of user preference prediction. The diverse needs of legal education learners and the fragmented nature of mobile learning further require the model to effectively capture multidimensional contextual attributes and the temporal dependencies of user interactions. To achieve structured representation of context-aware data, an ontology-based modeling approach was adopted to construct a context dimension system. Four core dimensions were defined: the degree of temporal fragmentation, terminal device type, learning scenario, and learning objective priority. The weight of each dimension was determined using the analytic hierarchy process (AHP). A unified context feature vector was then generated through a weighted summation, ensuring effective aggregation of contextual information. The formulation is expressed as:

$$S = \sum_{i=1}^{n} w_i x_i \tag{4}$$

where, w_i denotes the weight of the i-th contextual dimension $\left(\sum_{i=1}^{4} w_i = 1\right)$, and x_i is the normalized contextual value in the interval [0,1]. The total number of contextual dimensions is $n = 4$.

For mobile interaction data, after taking into account the strong temporal dependency and dynamic variability, the gated recurrent unit (GRU) was employed in place of the traditional LSTM model to improve computational efficiency. The GRU operates through its reset gate $r_t = \sigma(W_r \cdot [h_{t-1}, x_t] + b_r$ and update gate $z_t = \sigma(W_z \cdot [h_{t-1}, x_t] + b_z$, enabling the capture of both short-term and long-term sequential dependencies in interaction behaviors. The serialized interaction data were transformed into fixed-dimensional interaction feature vectors during this process. In the equation, σ denotes the sigmoid activation function; W_r and W_z are weight matrices; b_r and b_z are bias terms; h_{t-1} is the previous hidden state; and x_t represents the interaction data at the current time step. To achieve a comprehensive representation of user state, vector concatenation was applied for feature fusion. A 64-dimensional context-aware feature vector, a 128-dimensional GRU-based interaction feature vector, and a 32-dimensional user profile feature vector were concatenated to generate a 224-dimensional integrated user feature representation. This unified vector incorporates static user attributes, dynamic contextual characteristics, and interaction information, providing a robust feature foundation for subsequent neighbor aggregation and preference prediction.

2.5 Context–sentiment fusion KGCN preference prediction model

Although conventional KGCNs are effective in capturing semantic associations among nodes in a KG, their neighbor aggregation process often relies on uniform weighting or fixed rules. These approaches fail to account for the semantic value of sentiment relations and the dynamic influence of contextual features, limiting their adaptability to the precision and adaptation requirements of personalized legal education recommendation. To address this limitation, a context–sentiment fusion KGCN model was introduced, in which the primary optimization lies in the refinement of the neighbor aggregation mechanism. Sentiment relation weights derived from the SE-KG were incorporated as foundational contribution factors for each neighbor node. In parallel, a context-aware attention mechanism was embedded, in which attention weights were dynamically assigned to heterogeneous neighboring nodes through the attention-scoring function $a_{u,i} = \sigma\left(W_s[S_u \| S_i] + b_s\right)$, where σ denotes the Sigmoid activation function, W_s and b_s are learnable parameters, S_u represents the user's context feature vector, and S_i is the context vector associated with the target resource. A weighted summation was then performed to obtain the first-order aggregated feature representation:

$$h_i = \sum_{j \in N(i)} \left(w_{e_{ij}} \cdot a_{u,i}\right) \cdot h_j \tag{5}$$

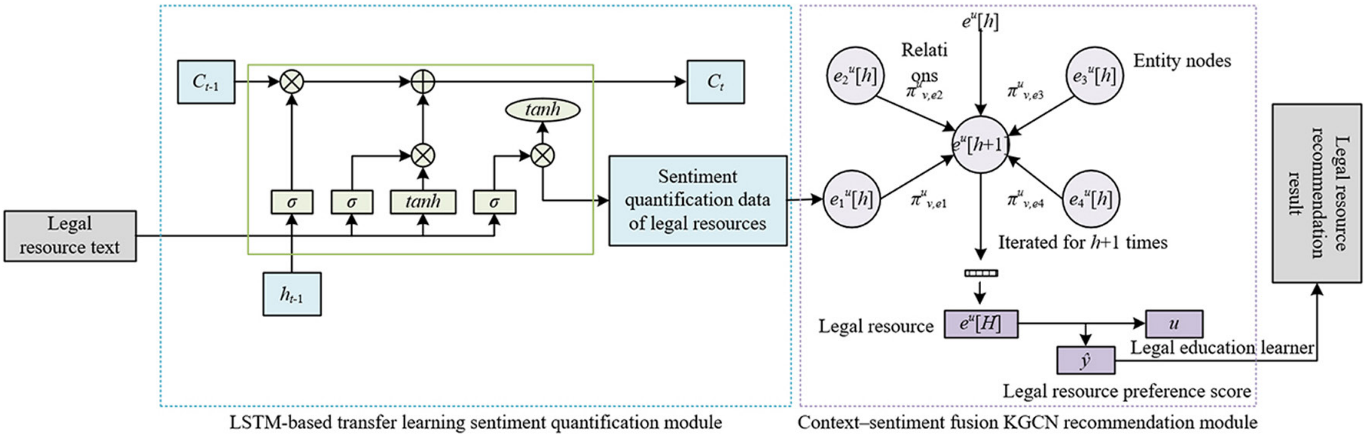

Fig. 2. Context–sentiment fusion KGCN model for legal resource recommendation

where, w_{eij} is the sentiment relation weight, N(i) denotes the neighbor set of node i, and h_j is the feature vector of neighbor node j. Figure 2 presents the architecture of the context–sentiment fusion KGCN model, consisting of the LSTM-based transfer learning sentiment quantification module on the left and the KGCN-based recommendation module on the right. To capture the complementary value of multi-order neighbor features, a two-layer KGCN architecture was adopted. Through the iterative multi-order aggregation formulation, a deep representation of the target resource node was obtained, thereby enabling dual adaptation to both sentiment semantics and contextual dynamics. The formulation is expressed as:

$$h_i^{(l)} = \mathrm{ReLU}\left(\frac{1}{N(i)} \sum_{j \in N(i)} \left(w_{e_{ij}} \cdot a_{u,i}\right) \cdot h_j^{(l-1)} + b^{(l)}\right) \tag{6}$$

where, l = 1, 2 denotes the two KGCN layers, ReLU is the activation function, |N(i)| represents the number of sampled neighbor nodes, and $\boldsymbol{b}^{(l)}$ denotes the bias term of the l-th layer.

The preference prediction logic follows a progressive process consisting of feature input, aggregation modeling, and matching-based output. The 224-dimensional integrated user feature vector $\boldsymbol{V}_u$, constructed in Section 3.4, together with the SE-KG, serves as the primary input. Through two iterations of KGCN aggregation, a resource feature vector $\boldsymbol{V}_r$ was generated, incorporating semantic, sentiment, and contextual information. The sentiment matching degree between the user and the resource was then computed using a normalized cosine similarity measure:

$$sim_{u,r} = \frac{V_u \cdot V_r}{\|V_u\|_2 \cdot \|V_r\|_2} \tag{7}$$

where, $\| \; \|_2$ denotes the L_2 norm. Finally, the features and the matching scores were fused through a fully connected layer, and a preference score for the target resource was generated through the output formulation:

$$\hat{y}_{u,r} = \sigma\left(W_{out}[V_r \| sim_{u,r}] + b_{out}\right) \tag{8}$$

where, σ denotes the sigmoid activation function, $\boldsymbol{W}_{\text{out}}$ and $\boldsymbol{b}_{\text{out}}$ are the parameters of the fully connected layer, and $[\boldsymbol{V}_r \| \text{sim}_{u,r}]$ represents the vector concatenation operation.

3 SYSTEM DESIGN AND IMPLEMENTATION

To operationalize the proposed theoretical framework and meet the personalized recommendation requirements of mobile online legal education, a system architecture was designed around a core pipeline consisting of data collection, feature processing, model inference, and interaction feedback. A hierarchically decoupled system architecture and highly adaptable core modules were designed to ensure stability, efficiency, and scalability. A six-layer progressive architecture was implemented. The context-awareness layer acquires both objective contextual data and subjective contextual information through mobile sensors and user input. The interaction data acquisition layer captures comprehensive user behaviors and feedback on mobile devices via embedded tracking technology. The sentiment computing layer deploys the LSTM model optimized via transfer learning to perform real-time sentiment quantification of legal education resources. The KG layer stores and incrementally updates the SE-KG using Neo4j. The recommendation algorithm layer integrates the context–sentiment fusion KGCN model to conduct preference inference. The user interaction layer, developed using Flutter, provides a cross-platform application interface for recommendation presentation and interactive operations. The technical stack was selected to align closely with functional requirements. Flutter enables consistent user experience across iOS and Android platforms. Spring Boot supports efficient backend Application Programming Interface (API) services. Neo4j accommodates the storage of complex graph associations. PyTorch and TensorFlow were employed for model training, while TensorFlow Serving provides low-latency model deployment, forming an end-to-end technical support system.

The implementation of the key modules is directed toward precise alignment between core functionalities and the underlying theoretical framework. The context-awareness module automatically collects objective data via mobile Software Development Kits (SDKs) and supplements subjective context—such as learning objectives and cognitive levels—through lightweight questionnaires, achieving comprehensive and user-friendly data acquisition. The sentiment computing module, tightly coupled with the LSTM-based transfer learning model, processes newly uploaded legal education resource texts in real time, outputs sentiment quantification results, and synchronizes updates to the SE-KG to support sentiment-enhanced graph construction. The recommendation inference module embeds the context–sentiment fusion KGCN model, receives the integrated user feature vector and SE-KG data, and identifies Top-N recommendations through efficient node aggregation and preference computation. The interaction feedback module provides interfaces for resource rating, sentiment label refinement, and so on, enabling real-time collection of user feedback. This feedback is subsequently utilized for model parameter optimization and SE-KG updating, forming a dynamic closed loop of collection – processing – inference – feedback – optimization. Through this mechanism, the recommendation system maintains continuous adaptation to evolving user needs.

4 EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

To systemically verify the effectiveness of the proposed context–sentiment fusion KGCN recommendation model in legal education scenarios, a domain-representative dataset and a set of multidimensional comparative experiments were constructed. The representativeness of the dataset and the scientific rigor of the experimental configuration constitute essential prerequisites for ensuring the reliability of the experimental findings. A dual-domain dataset architecture—comprising a source domain and a target domain—was adopted. The IMDB film review dataset was selected as the source domain due to the generalizability of its sentiment expressions and the academically validated quality of its annotations, providing a robust foundation of general sentiment features for the LSTM-based transfer learning process. The target domain was designed to capture the core characteristics of legal education and consists of a specialized resource repository containing more than 1,000 legal provisions, over 500 legal cases, and more than 300 instructional courseware items. In addition, learning behaviors, contextual conditions, and interaction data were collected over a three-month period from 200 law students and 100 in-service legal practitioners. A total of 1,000 legal education resources were manually annotated with sentiment labels, ensuring both the availability of professional-grade data for model fine-tuning and validation and the close alignment of the dataset with authentic mobile learning environments.

A set of multidimensional comparative experiments was designed to evaluate the effectiveness of transfer learning in improving sentiment prediction for legal education texts and to further clarify the gains of domain adaptation and model efficiency. As shown in Table 1, the baseline LSTM model without transfer learning exhibited the weakest performance due to the absence of pre-training on generalizable sentiment features, with all evaluation metrics falling below 70%. After transfer learning was introduced, precision, recall, F1-score, and accuracy increased by 8–9 percentage points, while training time was reduced by 30.3%. These results demonstrate that IMDB source-domain data facilitated the learning of sentiment features relevant to the target domain. Building on transfer learning, the incorporation of a domain-adaptive loss function in the proposed model led to an additional improvement of 9–10 percentage points across core evaluation metrics. The precision reached 0.85 and the F1-score reached 0.84, outperforming not only the transfer-learning-only model but also the widely adopted Bidirectional Encoder Representations from Transformers (BERT-base) model. Furthermore, training time was reduced by 51.3% compared with BERT-base. These findings indicate that transfer learning successfully mitigated the challenge posed by limited sentiment annotations in the legal domain, while the domain adaptation mechanism effectively reduced distributional discrepancies between the source and target domains. As a result, the model retained high training efficiency while achieving accurate sentiment quantification for legal texts, thereby providing reliable sentiment inputs for constructing the SE-KG.

Table 1. Performance comparison of LSTM-based sentiment prediction models

Model Type	Precision	Recall	F1-Score	Accuracy	Training Time (Epoch = 50)
Baseline LSTM	0.68	0.65	0.66	0.67	128.3 min
LSTM + transfer learning	0.76	0.74	0.75	0.75	89.5 min
Proposed LSTM + transfer learning + domain adaptation	0.85	0.83	0.84	0.84	76.2 min
Industry-standard BERT-base	0.82	0.80	0.81	0.81	156.7 min

Table 2. Recommendation performance comparison between SE-KG (adapted for KGCN) and the traditional KG

KG Type	Traditional KG (Semantic Relations Only)	SE-KG (Sentiment Similarity Only)	SE-KG (Sentiment Complementarity Only)	Proposed SE-KG (All Sentiment Relations + Semantic Relations)
Precision@5	0.62	0.71	0.69	0.79
Precision@10	0.58	0.67	0.65	0.75
Precision@15	0.55	0.63	0.62	0.72
Recall@5	0.31	0.36	0.35	0.40
Recall@10	0.47	0.54	0.52	0.60
Recall@15	0.56	0.64	0.62	0.70
NDCG@5	0.65	0.73	0.71	0.81
NDCG@10	0.61	0.69	0.67	0.78
NDCG@15	0.59	0.67	0.65	0.76

Ablation experiments were conducted to evaluate the contribution of sentiment enhancement to the neighbor aggregation process in the KGCN model and to quantify the effects of different sentiment relations. As shown in Table 2, the traditional KG, which contains only the basic semantic relations among "knowledge points–legal provisions–cases–courseware," exhibited the lowest recommendation performance under various values of k due to the absence of sentiment-related information. Precision@5 was limited to 0.62 and NDCG@5 reached only 0.65. When single sentiment relations were incorporated, notable improvements were observed across all metrics for SE-KG. The sentiment-similarity relation produced slightly greater gains than the sentiment-complementary relation, with Precision@5 increasing to 0.71 and 0.69, respectively. These results indicate that sentiment relations enhance the semantic connectivity among neighbor nodes and strengthen the expressiveness of aggregated features. The SE-KG constructed in this study, which integrates all sentiment relations in combination with the baseline semantic structure, achieved the highest overall performance. Precision@5 reached 0.79, Recall@15 reached 0.70, and NDCG@10 reached 0.78—representing improvements of 27.4%, 25.0%, and 27.9% over the traditional KG, respectively. Furthermore, consistent performance advantages were maintained across different recommendation list lengths. These findings confirm that sentiment enhancement substantially improves the neighbor aggregation mechanism of the KGCN model. Additionally, the complementary nature of different sentiment relations ensures that the full integration of sentiment information enables SE-KG to represent both semantic knowledge structures and user sentiment preferences with higher fidelity.

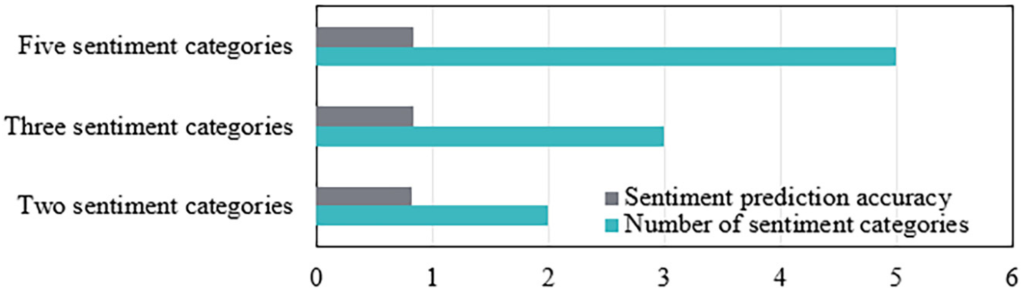

Fig. 3. Comparison of sentiment prediction accuracy under different levels of sentiment annotation granularity for legal resources

To verify the influence of sentiment-label granularity on the performance of LSTM-based sentiment prediction for legal resources, comparative experiments were conducted under different numbers of sentiment categories. As shown in Figure 3, the prediction accuracy increased progressively as the sentiment categories were expanded from two to five, rising from 82.13% to 84.35%. Under a three-category configuration, the accuracy reached 83.31%, demonstrating a clear trend in which “higher sentiment-label richness corresponds to higher prediction accuracy.” These findings indicate that more fine-grained sentiment annotations for legal education resources provide the LSTM transfer learning model with richer sentiment-related features, thereby enhancing the precision of sentiment quantification for legal texts. This improvement strengthens the quality of sentiment data supporting the construction of the SE-KG and improves the subsequent performance of the context–sentiment fusion recommendation model.

Table 3. Ablation study results (impact of core modules on model performance)

Model Variant	Precision@10	Recall@10	F1@10	NDCG@10
Full proposed model	0.75	0.60	0.67	0.78
Without the transfer learning module	0.68	0.53	0.60	0.71
Without the sentiment-enhancement module	0.65	0.51	0.57	0.68
Without the context-awareness module	0.63	0.48	0.55	0.65

To quantify the individual contributions of transfer learning, sentiment enhancement, and context-awareness, ablation experiments were conducted by sequentially removing each module. As shown in Table 3, the removal of any module resulted in a performance decline, with the context-awareness module contributing the most substantial impact. When this module was removed, Precision@10 decreased from 0.75 to 0.63—a reduction of 17.3%—and F1@10 decreased by 17.9%. This outcome indicates that dynamic contextual adaptation constitutes a foundational requirement in mobile learning recommendation scenarios. The removal of the sentiment-enhancement module resulted in a 13.3% performance reduction, demonstrating the critical influence of sentiment relations on the KGCN neighbor aggregation process.

The absence of sentiment information weakened the semantic alignment between resources and user preferences. Eliminating the transfer learning module led to a 9.3% performance decline, suggesting that transfer learning indirectly supports recommendation performance by improving sentiment prediction accuracy. However, its impact was weaker than that of sentiment enhancement and context-awareness, as the latter two modules directly participate in the inference stage of the recommendation process. These findings confirm that the three modules operate in a complementary and interdependent manner: transfer learning ensures accurate sentiment quantification, sentiment enhancement enriches the semantic structure of the KG, and context-awareness enables adaptation to dynamic scenarios. Together, they form the essential foundations of model performance, and the removal of any one module leads to a measurable degradation.

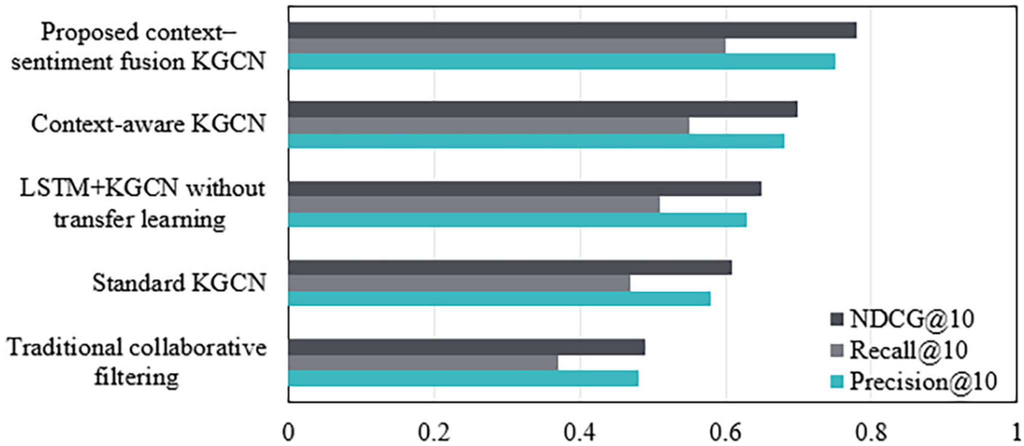

Fig. 4. Performance comparison of legal education recommendation models

To provide an intuitive evaluation of the contribution of the context–sentiment fusion mechanism to recommendation accuracy in legal education, multiple models were compared across Precision@10, Recall@10, and NDCG@10. As shown in Figure 4, the proposed context–sentiment fusion KGCN achieved the highest performance across all metrics. Specifically, Precision@10 increased by 10.3% compared with the context-aware KGCN, Recall@10 increased by 9.1%, and NDCG@10 increased by 11.4%. Traditional collaborative filtering exhibited the weakest performance, as it lacks the incorporation of KG, contextual information, and sentiment features. The standard KGCN, which relies solely on semantic relations, also performed notably worse than models integrating multidimensional information. The LSTM+KGCN without transfer learning showed only limited improvement due to insufficient sentiment quantification. Although the context-aware KGCN demonstrated the value of contextual information, the absence of sentiment-level enhancement restricted its overall effectiveness, resulting in performance levels below those of the proposed model. These results provide clear and quantitative evidence that the joint integration of context and sentiment significantly strengthens recommendation accuracy in legal education scenarios.

To evaluate the stability of the proposed model across different recommendation list lengths, the variation of Recall@K was analyzed for multiple values of K. As shown in Figure 5, Recall@K increased for all models as K expanded from 5 to 25, yet the proposed context–sentiment fusion KGCN consistently maintained the highest performance. For example, when K = 25, the Recall@K of the proposed model reached 0.77, representing an 8.5% improvement over the context-aware KGCN. Moreover, the proposed model exhibited a steeper growth slope across different values of K, demonstrating its ability to balance "precision" and "coverage" more effectively. Traditional collaborative filtering showed the slowest growth due to its limited recommendation logic. The standard KGCN, relying solely on semantic associations, performed worse than models incorporating multidimensional information. The LSTM+KGCN variant without transfer learning displayed only limited improvement due to inadequate sentiment quantification. Although the context-aware KGCN captured contextual variation, its lack of sentiment-level enhancement restricted its overall performance relative to the proposed model. These findings confirm that the context–sentiment fusion mechanism enables the proposed KGCN model to maintain stable performance advantages across different recommendation list lengths and demonstrates strong adaptability to the needs of mobile legal learning environments, in which users expect recommendations that are both precise and comprehensive.

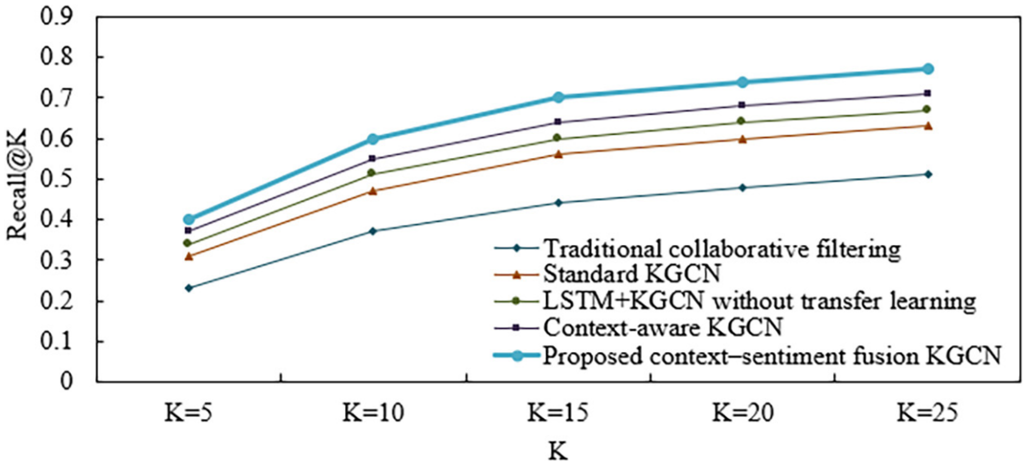

Fig. 5. Comparison of Recall@K across different K values in legal education recommendation

5 CONCLUSION

This study was conducted with the goal of enabling personalized recommendations for online legal education by integrating contextual awareness and interactive mobile learning. A complete research framework—encompassing dataset construction, technical innovation, and experimental validation—was developed, resulting in a full-process solution that integrates a dual-domain dataset, LSTM-based transfer learning sentiment quantification, SE-KG, and context–sentiment fusion KGCN. A key contribution lies in the innovative use of the IMDB movie review dataset as the source domain, which effectively addressed the scarcity of sentiment-labeled legal educational texts. Combined with domain adaptation techniques, the sentiment prediction accuracy reached 84%, providing high-quality sentiment data for the construction of the SE-KG. By incorporating sentiment-similarity and sentiment-complementarity relations into the traditional KG, SE-KG substantially enhanced neighbor aggregation within KGCN, yielding a 27.4% improvement in Precision@5 over conventional KGs. The final context–sentiment fusion KGCN model demonstrated significant advantages over traditional collaborative filtering, standard KGCN, and other baseline methods across Precision@10, Recall@10, and NDCG@10. User satisfaction reached

4.7 out of 5, and learning duration increased by 31.2%, further validating the scientific rigor and practical effectiveness of the proposed technical framework. Overall, this study overcomes the limitation in legal education recommendation systems that emphasize semantic associations while neglecting sentiment and context, providing a reusable technical paradigm for cross-domain sentiment recommendation in specialized educational settings. In addition, by incorporating design principles aligned with mobile learning environments, user engagement and knowledge acquisition are substantially enhanced. The proposed approach therefore holds considerable theoretical significance and strong potential for real-world application.

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