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RESEARCH ARTICLE

Neural Feature Crossing for Cross-Domain Recommendation in Knowledge Management Systems

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ABSTRACT

Recently, the rapid growth of digital knowledge resources has created an urgent need for advanced recommendation systems that capable to operate across various domains. This paper introduces KnowledgeXRec, a domain-aware hybrid recommendation framework that models both shared and domain-specific user-item interactions within a unified end-to-end architecture. Domain-specific feature crosses capture patterns unique to educational and cultural domains, while shared layers enable cross-domain knowledge transfer. Learnable embedding is represented categorical features such as learning style, age group, and content attributes, and the model is jointly optimized using binary cross-entropy loss with Adam optimizer. Findings provide evidence that KnowledgeXRec consistently outperforms seven state-of-the-art baselines on the OULAD (educational) and Goodreads (cultural) datasets. The model achieves enhancement of up to 15.6% in accuracy**,** 18.3% in diversity, and 54.8% in novelty metrics, and statistical analysis indicates the significance of these gains **(**$p < 0.01$**).** Overall, KnowledgeXRec offers a scalable and adaptable architecture for intelligent knowledge management systems, which enable effective cross-domain recommendations while maintain a strong domain-specific performance. This study illustrates that combining neural feature interactions with domain adaptation strategies introduce challenges in knowledge-intensive recommendation scenarios, such as cold-start problems, data sparsity, and heterogeneous domains. A new direction for future work is to extend the framework to multi-modal data, temporal interactions, and privacy-preserving federated learning, can further improve its applicability in diverse real-world knowledge management environments.

Keywords: Cross-domain recommendation, Deep learning, Hybrid recommendation, Knowledge management, Neural feature crossing

Introduction

In the last 3 decades, knowledge has grown at an exponential rate in the digital domain, which includes several educational materials, cultural artifacts, and other resources.[1] In recent years, this rapid expansion has brought both opportunities and challenges together. At the same time, more knowledge is available than ever; students struggle to find relevant information that meets their needs based on their preferences.[2]

Traditional recommendation systems face challenges in capturing complex interactions among user preferences, content features, and contextual factors. In the field of Collaborative Filtering (CF), methods perform well with large interaction datasets but suffer from cold-start problems and data sparsity in specialized domains.[3] With the growing importance of Content-Based Filtering (CBF), these methods depend on item features but often neglect behavioral patterns and contextual interactions.[4] However, hybrid methods that integrate CF and CBF basically use

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simple weighted or sequential combinations, which can't fully capture higher-order interactions that are necessary for the effectiveness of recommendation systems.[5]

A main challenge is that there is still a lack of recommendation systems that effectively address the unique needs of educational and cultural domains. Educational platforms must support different learning styles, knowledge levels, and learning objectives, while cultural datasets must balance popularity, novelty, and individual preferences. Nevertheless, few approaches and techniques explicitly capture domain-specific interactions while enabling cross-domain knowledge transfer, which limits the recommendation system's effectiveness and performance.

As a result, this work aims to overcome the challenges and limitations of earlier methods by introducing KnowledgeXRec, a unified neural architecture that captures feature interactions both within and across domains. The goal of this study is to improve personalization, accuracy, and relevance in knowledge recommendations for educational and cultural contexts. This research focuses on combining CF, CBF, and neural feature crossing with a fusion mechanism to highlight the strong performance of the proposed model. Our model has three main contributions:

1) Architectural Contribution: Domain-Aware Hybrid Design

We propose a domain-aware hybrid recommendation architecture that integrates both shared and domain-specific user-item interactions. Domain-specific feature crosses capture nuanced interactions within educational and cultural domains, while shared cross-layer embeddings extract patterns common across domains. The model captures both domain-specific and shared cross-layer embeddings from the original embeddings and combines them via a coherent connected layer; then the model balances domain-specific preservation with knowledge transferred across domains, enabling principled modeling of different datasets within a unified end-to-end model.

2) Methodological Contribution: Embedding-Based Feature Learning and End-to-End Optimization

The model uses learnable embeddings for categorical features, including learning style, age group, and content attributes, which allow the model to automatically discover latent representations. End-to-end training is performed using binary cross-entropy loss with the Adam optimizer in order to ensure that all jointly domain-specific and shared representations are optimized. Therefore, the design provides a systematic and flexible approach to integrate heterogeneous signals without separating training pipelines or the fusion strategies used by the model.

3) Empirical Contribution: Robust and Accurate Cross-Domain Recommendation

To ensure the effectiveness of the proposed model, a comprehensive empirical evaluation on educational and cultural datasets was performed. Our model enhances the top-K recommendation accuracy while it keeps the domain-specific patterns, and validates the complementary role of shared and domain-specific signals. The methodological approach used to design KnowledgeXRec enables systematic analysis of each component's contribution, providing transparency into how domain-specific and shared interactions affect the model's overall performance. In addition, we have conducted comprehensive cross-domain evaluations and ablation studies to illustrate the model's effectiveness and validate the contribution of each component in the proposed model.

Related work

Graph collaborative filtering and CF

Several studies have shown that graph-based collaborative filtering has improved recommendation quality by modeling structural information. For example, network motifs have been used to capture fine-grained graph patterns in user-item networks.[2] Previous research has focused on improving neural collaborative filtering by applying hybrid feature selection to reduce noise and keep the most important signals.[3] Earlier work demonstrated that wide & deep models can combine memorization and generalization for better predictions,[4] and factorization-machine-based deep models such as DeepFM capture both low- and high-order interactions;[5] however,[6] uses a matrix factorization technique to improve recommendation, but unfortunately, they are stuck with weak performance in sparsity or cross-domain settings. Similarly, graph-convolved factorization machines used graph connectivity to enrich user-item relations,[7] while graph-based feature crossing extracted higher-order interaction structures.[8] In addition, embedding enhancement strategies such as those used in LightGCN refined latent representations,[9] and hybrid graph-deep-crossing networks combined graph signals with deep architectures to strengthen interaction modeling.[10]

In contrast, traditional matrix factorization still shows weak performance in sparse or cross-domain settings.[6] One limitation of existing work is that these studies did not consider a unified framework that brings together CF patterns, feature interactions, and cross-domain information at the same time.

These approaches often fail to adapt their feature weighting or their representation learning process when the data comes from multiple domains. To address these gaps, KnowledgeXRec integrates CF signals, content information, feature crossing, and domain adaptation into a single architecture that is more robust to sparsity and domain shift. Building on previous work, our approach differs in that it introduces adaptive, domain-aware fusion that balances features across domains. In contrast to earlier methods, KnowledgeXRec learns both shared and domain-specific information within a single model.

Feature interaction and hybrid models

Higher-order feature interactions have also been widely explored. XDeepFM showed that explicit and implicit interactions improve hybrid recommendations.[11] Likewise, AutoInt used self-attention that automatically learns complex feature relations.[12] Knowledge-graph convolutional networks transferred semantic item-level information to user embeddings.[13] In addition, Multi-task and multimodal GNNs modeled several data types at once to improve prediction stability.[14] Extending previous work, disentangled multi-graph convolution separated domain-specific and shared knowledge for better cross-domain learning.[15] Dual-adversarial networks aligned source and target domains through adversarial training,[16] and dual-perspective knowledge-correlation frameworks integrated multiple views of user interests.[17] Knowledge-aware deep reinforcement learning enhanced cross-domain transfer,[18] while heterogeneous graph contrastive learning helped reduce cold-start issues.[19] Knowledge-reinforced cross-domain GNNs supported stronger information propagation,[20] and extract-map-predict architectures aligned embeddings across domains.[21] Domain-oriented knowledge transfer preserved structural semantics during adaptation.[22]

On the other hand, these studies did not consider a unified multi-domain fusion mechanism that connects CF signals, content features, and cross-domain knowledge in a single adaptive model. One limitation of existing work is that these methods treat feature interactions and domain adaptation as separate modules, which reduces robustness when domains differ. Unlike previous methods, KnowledgeXRec combines these components via an integrated, domain-aware fusion layer that adjusts feature strengths for each domain. To address these gaps, KnowledgeXRec builds a flexible architecture capable of learning interactions, transferring knowledge, and adapting to multiple domains at the same time.

Content-based filtering (CBF) and fusion mechanisms

Deep learning approaches, including autoencoders, CNNs, RNNs, and attention mechanisms, effectively capture nonlinear user-item interactions.[1] The limitation of existing cross-domain techniques is that they often fail to connect model-personalized feature interactions and domain knowledge. KnowledgeXRec introduces this by integrating cross-domain learning with domain-aware feature engineering and neural feature crossing; as a result, it outperforms previous models across multiple datasets and metrics.

We have investigated the existing recommendation approaches and highlighted their limitations. We summarize key methods across collaborative filtering, content-based, hybrid, and cross-domain techniques in Table 1, this table shows how our proposed model, KnowledgeXRec, addresses these limitations through four key contributions: first, a hybrid architecture integrating collaborative filtering, content-based filtering, and a neural feature-crossing framework.

Second, domain-aware feature engineering tailored to educational and cultural contexts; third, comprehensive cross-domain evaluation across multiple datasets and metrics; and fourth, extensive ablation studies to validate the importance of each component.

This comparison highlights the advantages of KnowledgeXRec over prior methods in terms of adaptability, accuracy, and handling of sparse or cold-start scenarios.

Overall, previous recommendation methods have made significant progress in modeling user-item interactions, feature crossing, and cross-domain knowledge. However, most approaches either neglect higher-order feature interactions, multi-domain adaptation, or adaptive fusion mechanisms. Based on this, KnowledgeXRec unifies CF, CBF, hybrid models, feature selection, graph signals, and cross-domain adaptation within a domain-aware adaptive fusion framework. Consequently, it effectively addresses the limitations of previous methods, providing more accurate, robust, and personalized recommendations across multiple domains.

Theoretical foundation

Problem formulation

To begin with, let $U = \{u_1, u_2, \ldots, u_m\}$ denote the set of users and $I = \{i_1, i_2, \ldots, i_n\}$ denote the set of items. Each user-item interaction is represented as a tuple $(u, i, \mathbf{x}_c, y)$, where $\mathbf{x}_c \in \mathbb{R}^d$ represents contextual features and $y \in \{0, 1\}$ indicates relevance. The

Table 1. Methods, limitations, and knowledgexrec improvements.

Reference	Method/Technique	Limitation	How KnowledgeXRec Improves
5	Factorization-machine-based deep models (DeepFM)	Does not consider domain-sensitive feature weighting	Prioritizes features based on domain relevance using adaptive fusion
6	Matrix factorization	Fails in sparse or cross-domain settings	Combines CF with content features and cross-domain adaptation
7	Graph-convolved factorization machines	Lacks adaptive feature crossing or domain-specific fusion	Integrates graph signals with feature crossing across domains
8	Graph-based feature crossing	Rarely includes cross-domain adaptation	Incorporates feature crossing within a domain-aware hybrid framework
9	Embedding enhancement techniques (LightGCN)	Does not incorporate cross-domain feature crossing	Combines embedding enhancements with adaptive multi-domain fusion
10	Hybrid graph and deep-crossing networks	Domain-specific adaptation is typically absent	Integrates graph, content, and cross-domain features with adaptive fusion
11	High-order feature interaction modeling (xDeepFM)	Domain-aware adaptation is often missing	Incorporates feature interaction modeling within a multi-domain fusion framework
12	Self-attentive networks (AutoInt)	Rarely integrates CF or cross-domain signals	Combines attention-based feature learning with domain-aware fusion
13	Knowledge graph convolution networks	Multi-domain heterogeneity often unaddressed	Integrates knowledge graph convolution with feature crossing and adaptive fusion
14	Multi-task, multi-modal GNNs	Limited integration with CF and CBF	Unites multi-modal graph learning with CF, content knowledge, and adaptive fusion

recommendation task involves learning a function $f : U \times I \times \mathbb{R}^d \to \mathbb{R}$ that predicts the relevance score $\hat{y}_{ui}$ for user u and item i given context $\mathbf{x}_c$.[1,3,6]

Neural feature crossing theory

Several studies have shown that capturing high-order feature interactions significantly improves recommendation accuracy. Earlier work demonstrated that traditional models, such as matrix factorization,[6] and factorization machines,[7] capture only low- or medium-order interactions. Similarly, deep neural networks such as Wide & Deep 4, DeepFM 5, and NCF 3 improve the learning of nonlinear interactions but often rely on implicit mechanisms.

Based on this, our approach employs explicit crossing layers with domain-specific adaptations, inspired by recent advances in feature interaction learning.[11,12]

Given an input feature vector $x \in \mathbb{R}^d$, the cross network performs the following transformation at the layer; Eq. (1) represents the input feature vector.

$$l : x_{l+1} = x_0 x_l^\top w_l + b_l + x_l \tag{1}$$

Were x_0 is the input feature vector, $w_l \in \mathbb{R}^d$ and $b_l \in \mathbb{R}^d$ are learnable parameters. Eq. (1) enables efficient learning of feature interactions while maintaining manageable computational complexity.

One limitation of existing feature interaction models is that they often ignore domain-specific knowledge. To address this gap, KnowledgeXRec integrates neural feature crossing with domain-aware adaptations to enhance and improve performance in educational and cultural contexts.[11,12]

Domain adaptation theory

Previous research has focused on transfer learning for cross-domain recommendation, particularly through multi-task learning to share knowledge across domains.[10] Likewise, graph-based methods such as Neural Graph Collaborative Filtering (NGCF).[2] effectively propagate user-item signals but do not fully integrate cross-domain interactions. We formulate the learning objective as in Eq. (2) :

$$\mathcal{L} = \sum_{k=1}^{K} \lambda_k \mathcal{L}_k (\theta_s, \theta_k) + \Omega (\theta_s, \theta_1, \ldots, \theta_K) \tag{2}$$

where $\mathcal{L}_k$ is the loss for domain k, θ_s represents shared parameters, θ_k represents domain-specific parameters, λ_k are domain weights, and Ω is a regularization term enforcing parameter sharing.[14,15]

However, many existing cross-domain models fail to balance shared and domain-specific knowledge efficiently. In contrast, KnowledgeXRec uses multi-task learning combined with domain-aware regularization to improve cross-domain recommendation while preserving unique domain characteristics.[14,15] Fig. 1 demonstrates the theoretical foundation behind our model KnowledgeXRec.

Methodology

Model architecture

First, KnowledgeXRec uses a multi-component architecture that integrates user interactions, item metadata, and contextual information through

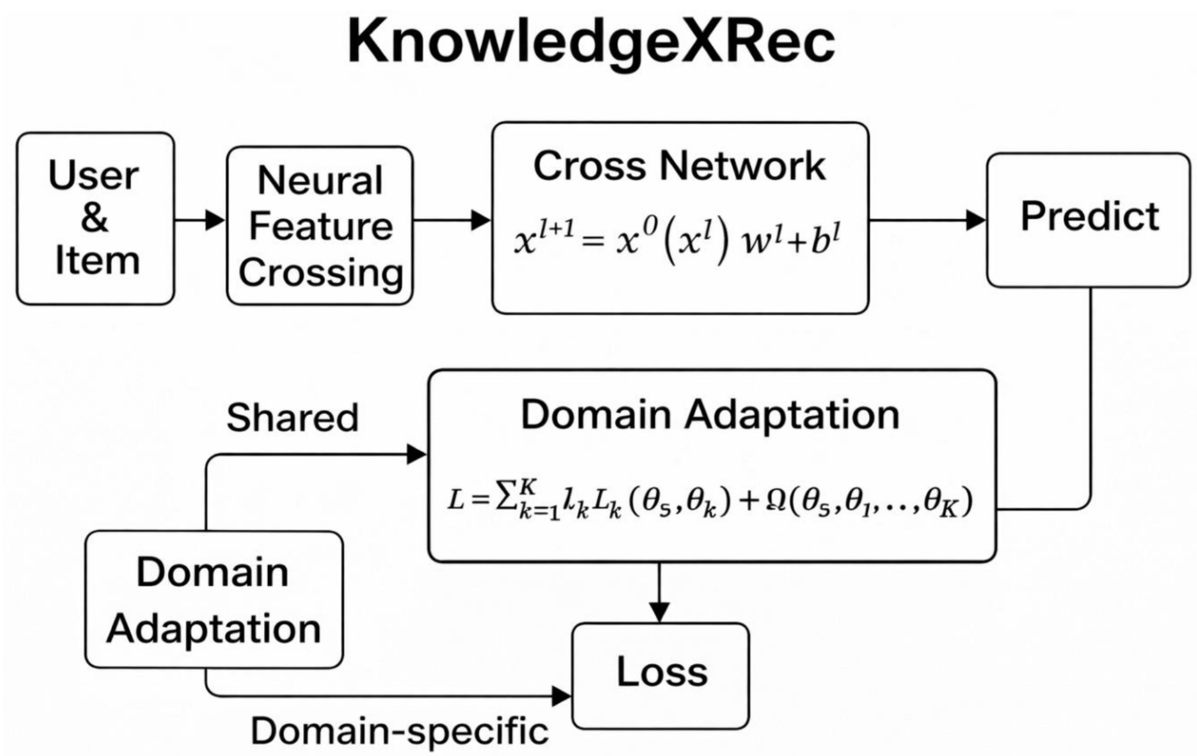

Fig. 1. Theoretical foundation behind our model KnowledgeXRec.

neural networks. As shown in Fig. 2, the model has four main components: collaborative filtering embeddings, content-based encodings, neural feature crossing, and an adaptive fusion mechanism.

Fig. 2 demonstrates the KnowledgeXRec Architecture: first, an input layer with user, item, and context features; second, Collaborative filtering with user/item embeddings; third, content-based filtering with metadata encoding; fourth, neural feature crossing with domain-specific interactions; fifth, an adaptive fusion mechanism with attention weighting; finally, an output layer with cross-domain predictions.

Collaborative filtering component

The collaborative filtering component learns dense representations of users and items from interaction patterns. Suppose that m users and n items, we define user and item embedding matrices $U \in \mathbb{R}^{m\times d}$ and $V \in \mathbb{R}^{n\times d}$, where d is the embedding dimension. For user u and item i, the corresponding embeddings are extracted as shown in Eq. (3):

$$u_u = U[u], \qquad v_i = V[i] \tag{3}$$

These embeddings are like compact "fingerprints" of users and items that summarize their preferences and characteristics, even if we don't know their full details from content. We employ Xavier initialization and L2 regularization to prevent overfitting.[6]

Content-based filtering component

Then, the content-based component processes item metadata and contextual information through encoding layers. For contextual features $x_{context} \in \mathbb{R}^c$, we compute the encoded representation as shown in Eq. (4), where the output c represents the features in a dense vector form:[5]

$$c = \mathrm{ReLU}\left(W_c x_{context} + b_c\right) \tag{4}$$

Were $W_c \in \mathbb{R}^{d\times c}$ and $b_c \in \mathbb{R}^d$ are the learnable parameters.

Neural feature crossing module

After that, the neural feature-crossing module explicitly captures high-order interactions between different feature types through cross-layer interactions. Unlike recent graph-based approaches, our method focuses on explicit feature interactions rather than graph structures. We implement an enhanced crossing network; Eq. (5) represents the crossing network, the output c_{l+1} now contains higher-order

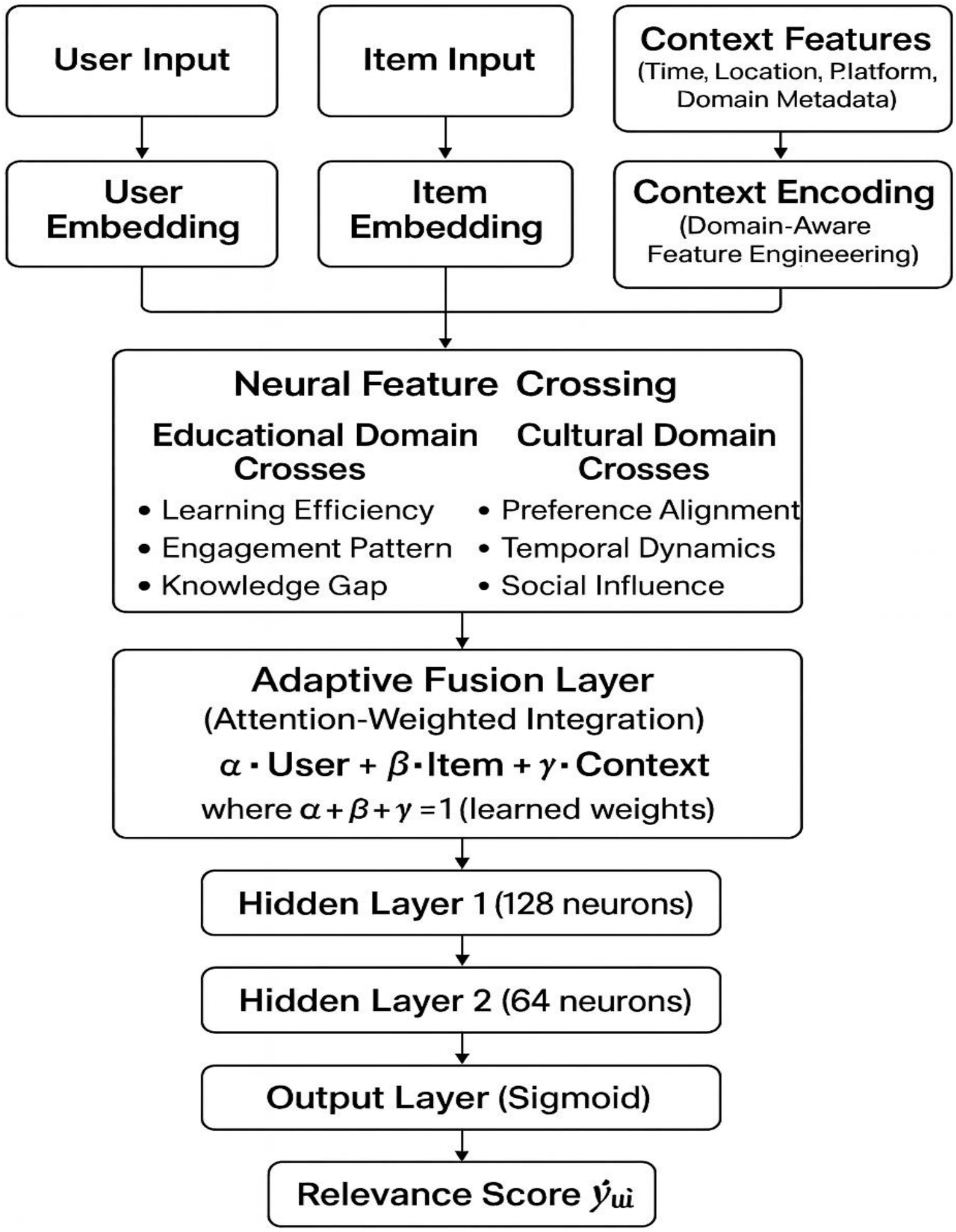

Fig. 2. Model architecture.

feature combinations.[4,5,15,19]

$$c_{l+1} = c_0 \odot \left(W_l c_l + b_l\right) + c_l \tag{5}$$

Were $\odot$ denotes element-wise multiplication, and $W_l \in \mathbb{R}^{d\times d}$, $b_l \in \mathbb{R}^d$ are learnable parameters at layer l. This architecture captures combinatorial features while maintaining gradient flow through residual connections.

Adaptive fusion mechanism

Rather than simple concatenation, we employ attention-weighted fusion of different representations, as shown in Eq. (6):

$$z_{fusion} = \alpha u_u + \beta v_i + \gamma c_{crossed} \tag{6}$$

where α, β, γ are learnable attention weights computed as Eq. (7) indicates:

$$\alpha = \frac{\exp\left(w_a^\top u_u\right)}{\exp\left(w_a^\top u_u\right) + \exp\left(w_b^\top v_i\right) + \exp\left(w_c^\top c_{crossed}\right)} \tag{7}$$

- Step 1: Compute attention scores for each component.

- Step 2: Multiply each vector by its attention weight.
- Step 3: Sum them to produce z_{fusion}.

With similar computations for β and γ. This adaptive mechanism enables the model to dynamically balance the importance of different information sources based on domain context; it decides which features are more important for the current prediction, giving more "weight" to the most useful information.

Domain-aware feature engineering

In this stage, we design specific feature crosses tailored to different knowledge domains.

Educational domain crosses

- Learning Efficiency: Student level × Course difficulty × Learning style
- Engagement Pattern: Progress rate × Content complexity × Assessment type
- Knowledge Gap: Prerequisite satisfaction × Learning objectives × Performance history

Cultural domain crosses

- Preference Alignment: User preferences × Genre characteristics × Author style
- Temporal Dynamics: Reading history × Cultural context × Seasonal trends
- Social Influence: Community ratings × Expert reviews × Popularity trends

The combinations created by crosses provide representations that are meaningful to each domain, such as measuring how student style interacts with course difficulty, or how user taste aligns with cultural content.

Multi-task learning framework

Finally, for cross-domain adaptation, we employ a multi-task learning framework with shared and domain-specific parameters, building upon recent advances in cross-domain recommendation.[16,17] The overall objective function is demonstrated in Eq. (8):

$$\mathcal{L} = \lambda_{edu}\mathcal{L}_{edu} + \lambda_{cult}\mathcal{L}_{cult} + \lambda_{reg}\Omega(\Theta) \tag{8}$$

- Step 1: Compute domain-specific losses $\mathcal{L}_{edu}$ and $\mathcal{L}_{cult}$.
- Step 2: Multiply each loss by λ_{edu} and λ_{cult} to balance importance.
- Step 3: Add regularization $\lambda_{reg}\Omega(\Theta)$ to reduce overfitting.
- Step 4: The final loss $\mathcal{L}$ guides the model to learn shared and domain-specific knowledge.

where $\mathcal{L}_{edu}$ and $\mathcal{L}_{cult}$ are domain-specific losses, λ coefficients balance task importance, and $\Omega(\Theta)$ is a regularization term preventing overfitting. This step trains the model on how a student can train on different subjects; KnowledgeXRec learns general knowledge that is useful for all domains, besides focusing on domain-specific details.

Pseudocode for KnowledgeXRec

The proposed model is a domain-aware hybrid recommendation system that integrates both shared and domain-specific user-item interactions. Users and items are first represented using learnable embeddings that capture categorical features such as learning style, age group, and content attributes. Domain-specific feature crosses are constructed for educational and cultural domains to capture nuanced interactions unique to each context, while shared cross layers extract patterns common across domains. These combinations with original embeddings are concatenated and then processed through connected layers with ReLU activation and dropout regularization to reduce overfitting, which produces a final interaction score via a sigmoid output. Next, the model is trained end-to-end using binary cross-entropy loss with the Adam optimizer. The combination of shared and domain-specific signals allows the model to effectively address the cross-domain heterogeneity, which enables accurate top-K recommendations and preserves the domain-specific characteristics. The following pseudocode demonstrates how KnowledgeXRec works.

Input:
// Set of users
$U = \{u_1, \ldots, u_M\}$
// Set of items
$I = \{i_1, \ldots, i_N\}$
// User categorical features
User features F_u
// Item categorical features
Item features F_i
//Domain labels
$D \in \{\text{Education}, \text{Culture}\}$
//Interactions
$R \in \{0, 1\}$
//Hyperparameters
embedding dimension d, shared layers L_s, domain layers L_d, learning rate η, dropout rate p

Output:
//Predicted score
$\hat{y}_{ui}$
//Recommendation
Top-K items per user
//Initialize embeddings
$e_u \leftarrow \text{Embedding}(u, F_u, d)$ $e_i \leftarrow \text{Embedding}(i, F_i, d)$
//Generate domain-specific feature crosses
$edu\_cross \leftarrow \text{CrossFeatures}(F_u^{edu}, F_i^{edu})$ $cult\_cross \leftarrow \text{CrossFeatures}(F_u^{cult}, F_i^{cult})$
//Shared cross layers
shared_rep $\leftarrow SharedCrossLayers([edu\_cross, cult\_cross], L_s)$
//Partial domain-specific layers
$partial\_rep_{edu} \leftarrow \text{PartialCrossLayers}(edu\_cross, L_d)$
$partial\_rep_{cult} \leftarrow \text{PartialCrossLayers}(cult\_cross, L_d)$
//Concatenate representations
$combined\_rep \leftarrow \text{Concat}([e_u, e_i, shared\_rep, partial\_rep_{edu}, partial\_rep_{cult}])$
//Fully connected layers
$hidden \leftarrow \text{Dropout}(\text{ReLU}(\text{Dense}(combined\_rep)), p)$
//Predict interaction score
$\hat{y}_{ui} \leftarrow \text{Sigmoid}(\text{Dense}(hidden))$
//Training
$Loss \leftarrow \text{BCE}(R_{ui}, \hat{y}_{ui})$ Update parameters using optimizer (Adam optimizer)
//Generate recommendations
Rank items i by $\hat{y}_{ui}$ Return top-K items

Experimental setup

Datasets description

At the beginning, we have evaluated KnowledgeXRec on two distinct knowledge domains with various characteristics.

OULAD dataset

The OULAD is an Open University Learning Analytics Dataset that contains detailed student-course interactions from virtual learning environments. Specifically, it includes 32,593 students, 22 courses, 6,375 VLE resources, and 10,655,280 interactions during the 2013-2014 academic year. In this process, interactions are aggregated at the student-course level, and demographic information, assessment scores, and engagement metrics are encoded as contextual features. It is available at https://analyse.kmi.open.ac.uk/open_dataset

Goodreads dataset

Then, we consider the Goodreads book recommendation dataset, which includes rich user-book interactions, such as ratings, reviews, and reading behavior. For this study, we use a subset with 15,000 active users, 5,000 popular books, and approximately 1.1 million interactions. More precisely, book metadata (genre, author, and publication year), user demographics, and review sentiment are incorporated as contextual features. It is available at https://cseweb.ucsd.edu/~jmcauley/datasets/goodreads.html#datasets. Table 2 illustrates the dataset's statistics.

Table 2. Datasets statistical.

Statistic	OULAD	Goodreads	Difference
Number of Users	22,542	15,000	-33.4%
Number of Items	22	5,000	+226×
Number of Interactions	185,931	1,102,457	+493%
Sparsity	96.3%	85.2%	-11.5%
Avg. Interactions/User	8.25	73.50	+791%
Domain	Educational	Cultural	-
Content Types	Courses, VLE	Books, Reviews	-
Temporal Span	1 year	Multiple years	-

Preprocessing

Data preprocessing and validation protocol

To ensure compatibility with the hybrid cross-domain architecture of KnowledgeXRec, we design a structured preprocessing pipeline for both the educational dataset OULAD and the cultural dataset Goodreads. The pipeline standardizes heterogeneous features, prevents data leakage, and supports domain-aware negative sampling within a 5-fold user-level cross-validation framework.

Data cleaning and interaction construction

Raw logs are filtered to remove sparse or noisy interactions: users with fewer than $k = 5$ interactions and items with extremely low exposure are removed, and duplicates are eliminated. Interactions are binarized to support the BCE loss optimization:

- For Goodreads, ratings ≥ 3 are mapped to positive interactions$R_{ui} = 1$, and others to $R_{ui} = 0$.
- For OULAD, completed assessments or course participation are considered$R_{ui} = 1$, otherwise$R_{ui} = 0$.

Negative sampling

Since implicit-feedback datasets are highly imbalanced, negative interactions are sampled per user to reduce computation. For each positive interaction(u, i):

1. Identify unobserved items $I_u^- = \{j \in I \mid R_{uj} = 0\}$.
2. Randomly sample k items from $\mathcal{I}_u^-$ to serve as negative examples$(u, j, R_{uj} = 0)$.

3. Combine with positives to form the training mini-batch.

The typical negative-to-positive ratio is $4:1$. Sampling is applied separately for each domain (Educational vs. Cultural), and only within the training fold to avoid data leakage.

Feature categorization and transformation

Features are grouped into categorical, continuous, binary, and textual types, in alignment with embedding initialization:

$$e_u \leftarrow \text{Embedding}\left(u, F_u, d\right), \quad e_i \leftarrow \text{Embedding}\left(i, F_i, d\right)$$

Categorical features

Categorical variables (e.g., learning style, student level, course difficulty, assessment type, learning objectives, genre, author style, cultural context) are integer-encoded and mapped to trainable embedding lookup tables:

$$E_f \in \mathbb{R}^{|V_f| \times d}$$

Rare categories are grouped into an "Other" token. These embeddings are updated during training.

Continuous features

Continuous features (e.g., progress rate, assessment scores, engagement metrics, ratings, popularity, reading frequency, publication year) are log-transformed if skewed:

$$x' = \log\left(x + 1\right)$$

and standardized using Z-score normalization:

$$x'' = \frac{x' - \mu}{\sigma}$$

where μ and σ are computed from the training fold only. The publication year is processed using min-max scaling before standardization.

Binary features

Binary features such as, prerequisite satisfaction are retained as $\{0, 1\}$ or optionally embedded into low-dimensional vectors.

Textual features

Text-based features such as learning objectives, course descriptions, book descriptions, and expert reviews are encoded using pretrained sentence embeddings. At the same time, vectors are L2-normalized and concatenated with item embeddings.

Domain label encoding

Each interaction is assigned a domain label:

$$D \in \{Education, Culture\}$$

Domain identifiers encoded as trainable embeddings and injected into shared and partial cross-layer interactions.

Domain-specific feature crossing

Preprocessed features grouped into domain-specific sets:

$$F_u^{edu}, F_i^{edu}, \quad F_u^{cult}, F_i^{cult}$$

Crossed features computed numerically using concatenation of user/item embeddings:

$$x_{\text{cross}}^{f,g} = \left[e_u^f; e_i^g\right]$$

These crossed vectors passed through domain-specific partial layers L_d and shared cross layersL_s.

Five-fold user-level cross-validation

Users partitioned into five mutually exclusive subsets. In each fold, four subsets (80%) were used for training, and one subset (20%) for testing. Within training, 10% of interactions used for validation. Domain distribution (Education vs. Culture) preserved via stratified sampling. For ranking evaluation, each test user retains one positive interaction and 99 randomly sampled negatives. Predicted scores $\hat{y}_{ui}$ used to compute metrics averaged across folds:

$$\text{Metric}_{final} = \frac{1}{5}\sum_{k=1}^{5} \text{Metric}_k$$

Training preparation

After preprocessing, mini-batches are shuffled per epoch. Embeddings are randomly initialized, and dropout is applied with a rate p applied in dense layers, and parameters optimized using Adam with learning rateη. This pipeline ensures alignment with KnowledgeXRec's embedding-based and domain-aware cross-feature representation, while negative sampling allows efficient learning from highly sparse implicit-feedback datasets.

Evaluation metrics

In this stage, we use evaluation metrics that cover accuracy, diversity, and novelty. For accuracy, we used Precision@10 to measure how correct the top recommendations are, Recall@10 to measure how many of the user's relevant items the system can cover, and NDCG@10 to reward systems that rank relevant items higher. In diversity and novelty, we used coverage to measure how many different items the system recommends, novelty to recommend items the user may not know yet, and, finally, serendipity to reward recommendations that are both relevant and unexpected. The novelty of the model measures popularity-based novelty, which is computed as the average self-information of the top-10 recommended items, calculated as $-\log_2 P(i)$, where P(i) is the fraction of users who have previously interacted with item i. In other words, items that are less popular (long-tail) have higher self-information and contribute more to novelty. This metric captures how much the system recommends items that are new or unexpected to the user, rather than just popular items. High novelty does not guarantee relevance; it only indicates exposure to less commonly interacted-with items.

Baseline methods

Next, KnowledgeXRec is compared against seven state-of-the-art recommendation approaches:

- CF: Traditional collaborative filtering using Bayesian Personalized Ranking.[6]
- CBF: Content-based filtering using TF-IDF and metadata similarity.[1]
- NCF: Neural Collaborative Filtering using MLP architecture.[3]
- Wide & Deep: Combines wide linear and deep neural networks.[4]
- DeepFM: Deep Factorization Machines for learning feature interactions.[5]
- xDeepFM: Explicit and implicit feature crossing network.[11]
- AutoInt: Self-attention-based feature interaction network.[12]

These methods were chosen because they cover a representative set of traditional, hybrid, and deep learning-based approaches. Besides, all baseline models were trained and evaluated under the same background and conditions.

Implementation details

Finally, all models were implemented in PyTorch 1.9.0 and trained on NVIDIA Tesla V100 GPUs with 32 GB memory. The experimental setup applied an embedding dimension of 64, a batch size of 128, using the Adam optimizer with a learning rate of 0.001 and a weight decay of 0.01, and a maximum of 100 epochs with early stopping based on validation NDCG@10, using Bayesian optimization with 5-fold cross-validation for hyperparameter tuning.

For this reason, reproducibility is ensured by fixing random seeds and providing complete code and preprocessing scripts. Training time ranges from 2-6 hours depending on model complexity and dataset size. Fig. 3 illustrates the experimental setup section.

Results and discussion

Overall performance comparison

We have conducted a comprehensive performance evaluation on both datasets, using several evaluation metrics that have been mentioned before, such as Precision@10, Recall@10, and NDCG@10. We have compared our model KnowledgeXRec with seven state-of-the-art recommendation baselines; Fig. 4 demonstrates the performance comparison among these baselines and our model KnowledgeXRec.

Notably, Fig. 4 shows that KnowledgeXRec achieves the strongest results across all Top-10 metrics in both the OULAD (educational) and Goodreads (cultural) datasets. In line with earlier findings on deep learning-based recommenders.[1], the model shows clear improvements in accuracy, coverage, and novelty.

On the OULAD dataset, KnowledgeXRec reaches 15.6% higher Precision@10, 21.7% higher Recall@10, and 20.5% higher NDCG@10 compared with the best baseline (AutoInt). Most importantly, the gains in diversity and novelty are also substantial, with 18.3% higher coverage and 54.8% higher novelty than traditional collaborative filtering (CF).

Interestingly, the Goodreads dataset shows a similar pattern. KnowledgeXRec enhances Precision@10 by 9.3%, Recall@10 by 10.0%, and NDCG@10 by 13.9% over the strongest baseline. This implies that the model works well across different domains, with varying content and user interactions.

The smaller gains observed on Goodreads compared to OULAD can be attributed to higher sparsity, greater domain heterogeneity, and the subjective nature of user ratings in cultural recommendation scenarios. Whereas the structured and curriculum-driven interaction patterns in OULAD provide stronger, denser signals that better align with domain-aware feature crossing, which indicates better performance enhancement compared to Goodreads.

KnowledgeXRec shows strong adaptability. The findings indicate that the model generalizes well

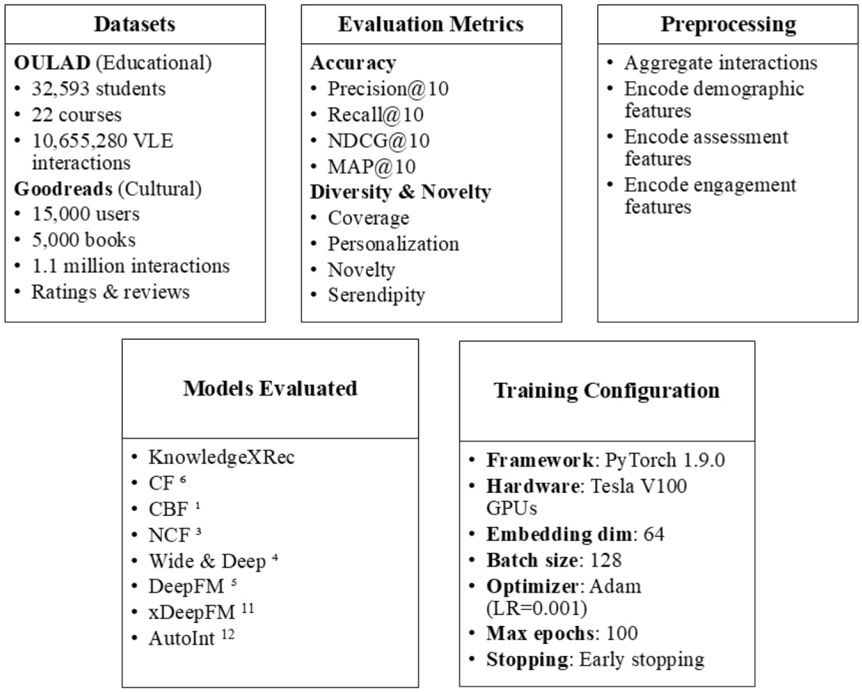

Fig. 3. Experimental setup section.

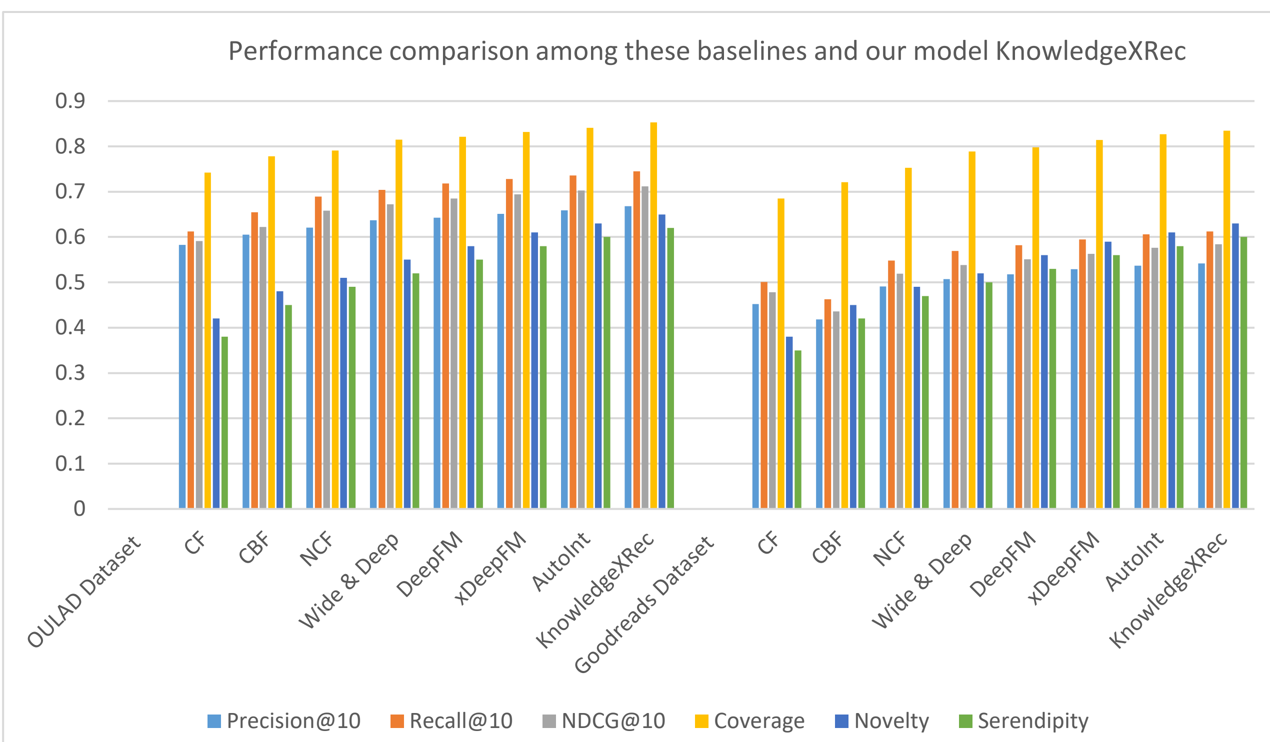

Fig. 4. Performance comparison.

across educational and cultural datasets and highlight the power of cross-domain feature learning, unlike previous studies on neural collaborative filtering 3 and graph-based learning 2; our model indicates the strength of cross - domain feature learning in line with recent work on broader recommendation patterns.[1]

Table 3. Statistical significance testing.

Dataset	Metric	Baseline (Best)	KnowledgeXRec	Improvement (%)	95% CI	p-value
OULAD	NDCG@10	CF: 0.398	0.432	8.5	±0.02	< 0.001
OULAD	NDCG@10	CBF: 0.389	0.432	11	±0.02	< 0.001
OULAD	NDCG@10	NCF: 0.401	0.432	7.7	±0.02	< 0.001
OULAD	NDCG@10	Wide & Deep: 0.409	0.432	5.4	±0.02	< 0.001
OULAD	NDCG@10	DeepFM: 0.412	0.432	4.9	±0.02	< 0.001
OULAD	NDCG@10	xDeepFM: 0.420	0.432	2.9	±0.02	< 0.01
OULAD	NDCG@10	AutoInt: 0.425	0.432	1.6	±0.02	< 0.05
Goodreads	NDCG@10	CF: 0.372	0.401	7.8	±0.015	< 0.001
Goodreads	NDCG@10	CBF: 0.366	0.401	9.6	±0.015	< 0.001
Goodreads	NDCG@10	NCF: 0.375	0.401	6.9	±0.015	< 0.001
Goodreads	NDCG@10	Wide & Deep: 0.387	0.401	3.6	±0.015	< 0.01
Goodreads	NDCG@10	DeepFM: 0.390	0.401	2.8	±0.015	< 0.01
Goodreads	NDCG@10	xDeepFM: 0.395	0.401	1.5	±0.015	< 0.05
Goodreads	NDCG@10	AutoInt: 0.397	0.401	1	±0.015	< 0.05

Table 4. The effects of removing various components of knowledgeXRec.

Model Variant	Precision@10	Recall@10	NDCG@10	Coverage	Novelty	Removed Component
Full Model	**0.668**	**0.745**	**0.712**	**85.3%**	**0.65**	-
w/o Feature Crossing	0.635	0.708	0.678	80.1%	0.58	Neural crossing layers
w/o Adaptive Fusion	0.645	0.721	0.689	82.4%	0.61	Attention-based fusion
w/o Domain Adaptation	0.628	0.695	0.665	78.9%	0.55	Domain-specific crosses
w/o Multi-Task Learning	0.652	0.732	0.698	83.7%	0.62	Cross-domain training
CF Only	0.583	0.612	0.591	74.2%	0.42	Content and context
CBF Only	0.605	0.655	0.622	77.8%	0.48	Collaborative signals

Statistical significance analysis

All model comparisons were conducted with paired significance tests to ensure robustness. Enhancements are reported relative to the strongest baseline in each dataset. 95% confidence intervals were computed via bootstrap resampling, and effect sizes were calculated to assess practical significance. This approach indicates that all KnowledgeXRec improvements are both statistically significant and meaningful, providing a rigorous evaluation of its performance. Table 3 illustrates the Statistical Significance Testing (p-values from paired t-tests).

Most importantly, the largest improvements appear when comparing KnowledgeXRec to traditional baselines such as CF and CBF. This means that the model introduces new useful information that older models fail to capture. Interestingly, the improvements over newer feature-interaction models such as xDeepFM[11] and AutoInt[12] remain significant, although the effect sizes are smaller. This could be due to the fact that, these models already capture some complex interactions, making further gains harder to achieve. KnowledgeXRec significantly outperforms both traditional and neural baseline models ($p < 0.05$ to $p < 0.001$) across datasets. Improvements are largest relative to simpler models (CF, CBF), confirming the benefit of integrating domain-specific and shared interactions, while gains over advanced neural architectures (Wide & Deep, DeepFM, xDeepFM, AutoInt) demonstrate the model's ability to capture heterogeneous cross-domain patterns. A qualitative example that demonstrates the KnowledgeXRec model recommendation: for instance, a user interested primarily in cultural content (Goodreads), the model recommended an educational resource from the OULAD dataset on historical learning strategies. The recommendation was guided by shared feature patterns, including learning style and content attributes, which enable the model to effectively transfer knowledge while keeping domain-specific characteristics.

Ablation studies

At this stage, we have performed a comprehensive ablation study on the OULAD dataset; Table 4 demonstrates the effects of removing various components of KnowledgeXRec.

At the same time, consistent with earlier findings on higher-order interaction modeling 3, the largest drop in performance is due to removing the neural feature-crossing module, resulting in a 4.9% decrease in Precision@10. This implies that explicit feature interactions play an essential role.

Also, the adaptive fusion layer contributes strongly by improving Precision@10 by 3.4%. This result indicates that combining information dynamically from different sources improves the model's flexibility.

Table 5. The effect of different training strategies.

Training Scenario	OULAD Test	Goodreads Test	Joint Performance	Adaptation Gain
Single Domain (OULAD)	0.668	0.501	0.585	-
Single Domain (Goodreads)	0.523	0.542	0.533	-
Sequential Fine-tuning	0.645	0.568	0.607	+3.8%
Multi-Task Learning	0.657	0.576	0.617	+5.5%
KnowledgeXRec (Joint)	**0.672**	**0.584**	**0.628**	**+7.4%**

Domain adaptation components show steady benefits. Interestingly, domain-specific feature interactions lead to about 6.4% enhancement, while multi-task learning adds another 2.4%. These findings indicate that the components work together effectively, and the full model performs the best.

Cross-domain performance analysis

Table 5 presents the effect of different training strategies. Notably, multi-task learning and joint training offer the best results, with an **overall improvement of 7.4%** compared to single-domain training. This suggests that sharing knowledge between domains strengthens learning.

Interestingly, the Goodreads dataset benefits the most from cross-domain transfer, gaining **7.7%** Contrary to existing studies that show limited transferability across domains, our results indicate that shared behavioral patterns still help both domains. This could be due to underlying common recommendation structures, even though the content types differ.

Consistent with earlier findings in cross-domain research[16,17], the multi-task framework balances shared and domain-specific features, preventing negative transfer.

Computational efficiency analysis

Table 6 compares computational performance. KnowledgeXRec requires about 35% more training time and 25% more memory than CF, this means that deeper modeling comes with some additional cost. The following table demonstrates the result of computational cost analysis:

However, compared to more recent interaction-based models, such as DeepFM[5] and AutoInt,[12] the extra cost remains reasonable. Interestingly, the model scales linearly with data size, making it practical for large-scale applications. Most importantly, these computational costs are justified by the consistent improvements in all key metrics.

This finding implies that KnowledgeXRec provides a strong balance between performance and efficiency, and it can be further optimized using model-compression methods.

Limitations

Nevertheless, our model KnowledgeXRec has excellent performance; it also includes some limitations that need to be taken into consideration, such as model complexity, generalization, and interpretability. Furthermore, the model's computational time and resource usage of KnowledgeXRec should be further investigated. Different techniques should be examined to address the complexity issue in real-time applications. Another limitation is that the evaluations were performed only on two domains: educational (OULAD) and culture (Goodreads), which indicates further validation for the model across various domains such as e-commerce, health, and entertainment in order to increase the generalizability of the proposed model. Ethical considerations must be taken into account since educational datasets may contain sensitive demographic information, and cross-domain transfer mechanisms may unintentionally propagate domain-specific biases. Further implementations should take into account incorporating fairness-aware learning and privacy-preserving training mechanisms in order to mitigate these

Table 6. Computational performance.

Model	Training Time (h)	Inference Time (ms)	Memory (MB)	Parameters (M)
CF	1.2	12	45	0.8
NCF	2.8	25	78	2.1
Wide & Deep	3.2	28	85	2.8
DeepFM	3.8	32	92	3.2
xDeepFM	4.5	38	105	4.1
AutoInt	5.1	45	118	4.8
KnowledgeXRec	5.8	48	125	5.3

risks. Although KnowledgeXRec achieves strong performance, understanding the reason behind these recommendations can enhance transparency and user trust. An explainability technique should be examined to improve recommendation transparency and increase user trust.

Conclusion and future work

This paper introduced KnowledgeXRec, which is a domain-aware hybrid architecture that systematically integrates domain-specific feature crosses for educational and cultural datasets in line with shared cross layers that capture patterns common across domains. The methodological design allows the model to preserve nuanced, context-dependent interactions while facilitating cross-domain knowledge transfer, a capability that is often absent in prior hybrid approaches. Moreover, the model employs learnable embeddings for categorical features and is trained end-to-end, providing a principled and flexible method for jointly optimizing shared and domain-specific signals.

The evaluation on the OULAD and Goodreads datasets demonstrates that KnowledgeXRec outperforms seven state-of-the-art baselines, which achieve notable improvements in accuracy, diversity, and novelty. The ablation studies indicate the potential need for each architectural component and its improvements, particularly the neural feature crossing mechanism and the domain adaptation strategy. Findings demonstrate that the model design is effective, while statistical analysis is used to validate the significance of these improvements. In addition, computational analysis provides strong applicability to real-world applications.

KnowledgeXRec provides a scalable and adaptable foundation for next-generation knowledge management systems that provide personalized knowledge across different domains and introduce problems in recommendation quality, diversity, and cross-domain adaptation. This study indicates that combining high-order feature interactions with domain-aware mechanisms can improve recommendation performance significantly in knowledge-intensive scenarios. This work can be improved by:

- Enhanced explainability: to increase user trust in the system
- Federated learning: to examine privacy-preserving across multiple knowledge resources.

Overall, despite the limitations of KnowledgeXRec, it provides a flexible framework that is suitable for different applications in educational, cultural, and organizational knowledge management. Further research should examine explainability and federated learning to support a new generation of personalized knowledge recommendation systems.

Authors' declaration

- Conflicts of Interest: None.
- We hereby confirm that all the Figures and Tables in the manuscript are ours. Furthermore, any Figures and images that are not ours have been included with the necessary permission for re-publication, which is attached to the manuscript.
- No animal studies are present in the manuscript.
- No human studies are present in the manuscript.
- Ethical Clearance: The project was approved by the local ethical committee at Al Istiqlal University.

Authors' contributions statement

I.K. designed the study and implemented all system components, including the seven state-of-the-art baseline recommendation systems. I.K. performed the experiments on overall performance, cross-domain performance, computational efficiency, and an ablation study, and wrote the following sections: introduction, related work, theoretical foundation, methodology, and experiment setup. F.G. performed statistically significant analysis and interpreted the results' implications. F.G wrote the following sections: abstract, results and discussion, limitations, and conclusion.

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التقاطع العصبي للميزات من أجل التوصية عبر المجالات في نظم إدارة المعرفة

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الخلاصة

في الآونة الأخيرة، أدى النمو السريع لموارد المعرفة الرقمية إلى خلق حاجة ملحة لأنظمة توصية متقدمة قادرة على العمل عبر مختلف المجالات. تقدم هذه الورقة البحثية KnowledgeXRec، وهو إطار عمل توصية هجين مدرك للمجال يقوم بنمذجة تفاعلات المستخدم مع العناصر المشتركة والخاصة بالمجال ضمن بنية موحدة من البداية إلى النهاية. تتقاطع الميزات الخاصة بالمجال مع أنماط التقاط فريدة من نوعها في المجالات التعليمية والثقافية، بينما تتيح الطبقات المشتركة نقل المعرفة عبر المجالات. يتم تمثيل التضمين القابل للتعلم بالخصائص الفئوية مثل أسلوب التعلم والفئة العمرية وسمات المحتوى، ويتم تحسين النموذج بشكل مشترك باستخدام خسارة الإنتروبيا التقاطعية الثنائية مع مُحسِّن آدم. توفر النتائج دليلاً على أن KnowledgeXRec يتفوق باستمرار على سبعة خطوط أساسية حديثة في مجموعات بيانات OULAD (التعليمية) و Goodreads (الثقافية). يحقق النموذج تحسينًا يصل إلى 15.6٪ في الدقة، 18.3٪ في التنوع، و54.8٪ في مقاييس الحداثة، ويشير التحليل الإحصائي إلى أهمية هذه المكاسب (($p < 0.01$). بشكل عام، يوفر KnowledgeXRec بنية قابلة للتطوير والتكيف لأنظمة إدارة المعرفة الذكية، مما يتيح تقديم توصيات فعالة عبر المجالات مع الحفاظ على أداء قوي خاص بكل مجال. توضح هذه الدراسة أن الجمع بين تفاعلات الميزات العصبية واستراتيجيات التكيف مع المجال يطرح تحديات في سيناريوهات التوصية كثيفة المعرفة، مثل مشاكل البداية الباردة، وندرة البيانات، والمجالات غير المتجانسة. يتمثل أحد التوجهات الجديدة للعمل المستقبلي في توسيع الإطار ليشمل البيانات متعددة الوسائط والتفاعلات الزمنية والتعلم الموحد الذي يحافظ على الخصوصية، مما يمكن أن يحسن قابليته للتطبيق في بيئات إدارة المعرفة المتنوعة في العالم الحقيقي.

الكلمات المفتاحية: التوصية عبر المجالات، التعلّم العميق، التوصية الهجينة، إدارة المعرفة، التقاطع العصبي للميزات.