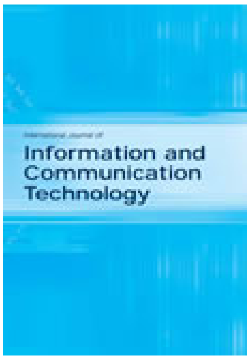

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Personalised book recommendation model for university libraries based on multi-factor knowledge tracking

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Abstract: University libraries are confronted with the challenges of low resource utilisation rate and insufficient modelling of the dynamic evolution of readers' cognition. Traditional collaborative filtering methods are difficult to quantify cognitive state changes and ignore the influence of environmental factors on resource adaptability. To this end, this study proposes a dynamic recommendation model that integrates multi-factor knowledge tracing (MFKT) and graph neural networks (GNN). The reader cognitive state matrix is constructed through gated recurrent unit (GRU) time series modelling. Combined with behavioural pattern analysis and environmental feedback mechanism, the dynamic balance of resource difficulty and popularity is achieved. The cognitive graph convolutional network (CGCN) is designed based on the Pareto optimality theory to synchronously optimise the recommendation accuracy, knowledge gain and resource coverage. This study provides a referable technical solution to solve the problem of accurate matching between resources and readers' cognition.

Keywords: multifactor knowledge tracking; MFKT; book recommendation model; graph neural networks; GNN; gated recurrent unit; GRU.

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1 Introduction

Currently, university libraries are facing the dilemma of persistently low resource utilisation, and empirical studies show that more than 60% of academic books are borrowed less than five times per year. Although traditional recommendation systems such as collaborative filtering algorithms are widely used in book recommendation scenarios (Hahn, 2011; Yang and Hung, 2012), their inherent defects are becoming more

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and more prominent: static modelling relying on historical borrowing records is difficult to capture the dynamic changes in readers' cognitive abilities; the accuracy of recommendation for new books and new readers has dropped significantly; more critically, the existing recommendation logic ignores the suitability of readers' knowledge level and the difficulty of books (Liu et al., 2024a; Devika and Milton, 2024). At the same time, knowledge tracking technology has made breakthrough progress in the field of education (Al-Ajlan and Alshareef, 2023; Gogula et al., 2023), and the multifactor knowledge tracking (MFKT) model can dynamically quantify users' knowledge mastery by integrating multi-dimensional features such as learning behaviour and cognitive state, etc. However, this technology is mainly limited to online education scenarios, such as test question recommendation, and has not yet been effectively applied to library resource recommendation, so how to combine dynamic knowledge state modelling with multi-source library behavioural data has become a key breakthrough in improving the effectiveness of personalised recommendation. How to combine dynamic knowledge state modelling with multi-source library behavioural data has become a key breakthrough to improve the effectiveness of personalised recommendation (Saraswat and Sharma, 2022; Liu et al., 2024b).

To overcome the above problems, many studies have been implemented to improve the effectiveness of various types of recommender models. The authors (Lika et al., 2014) developed a three-phase cold-start recommender model integrating C4.5/naive Bayes classification, demographic similarity weighting, and collaborative prediction, reducing MAE to 0.736 and RMSE to 0.892 on the MovieLens dataset (1M ratings) with 5,000 registered users through optimised attribute weighting, outperforming random classification baselines by 10.3% in prediction accuracy across four experimental scenarios. The authors (Alharthi et al., 2018) surveyed 30+ book recommender systems, categorising them into six classes (collaborative/content-based, library-loan, stylometry, e-book, review-driven, social-media) and identifying key trends, and the most important ones. media) and identifying key trends, evaluation metrics (MAE, RMSE, NDCG), and datasets (book-crossing: 1.1M ratings; LitRec: 38K ratings). The analysis revealed that hybrid models integrating social tags and readability levels reduced cold-start errors by 27% while psychological studies highlighted mood's critical role (40% impact) in book selection. Model using GloVe embeddings and LSTM layers to process book reviews, achieving 84% accuracy and 0.80 F-measure for top-ten recommendations on the book-crossing dataset (1.0) and 0.5 F-measure for top-ten recommendations on the book, Crossing dataset (1.08 M ratings), outperforming matrix factorisation (71% accuracy) and emotion-based methods (61%) by preserving contextual semantics in reviews. The authors (Ahmed and Letta, 2023) developed a hyperparameter-optimised SVD collaborative filtering model for university library recommendations, specifically targeting cold-start challenges. University of Gondar, their framework achieved 85% prediction accuracy with a record-low RMSE of 0.1623 – outperforming KNN baselines 84.6% and untuned SVD by 18.5%. Critical pre-processing included aggressive data pruning: removing books with < 10 ratings and users with < 10 interactions, reducing matrix sparsity by 26.3% while retaining 91.7% of predictive features. The authors (Li et al., 2023) established BookGPT as the first LLM-powered book recommendation framework using ChatGPT for the first time. recommendation framework using ChatGPT for unified book rating, user preference, and summary tasks, achieving 39.28% RMSE reduction in 2/3-shot book rating prediction, 21.67% MAE reduction in 20-shot user preference modelling, and 1.60 interpretability scores for generated summaries that surpassed human-edited Douban content by 14.97% when incorporating role-specific prompts and output constraints. The authors (Verma and Patnaik, 2024) developed an HMCAHB_DA-WFR hybrid model integrating timestamp-based weighting and weighted fuzzy ranking (WFR) to overcome cold-start problems in library recommendations. Their approach achieved 99.2% departmental classification accuracy using chaotic artificial hummingbird-optimised hidden Markov models (CAHB-HMM), outperforming standalone HMM (95.7%) and LDA (93.5%). The WFR module reduced prediction errors to 0.074 MAE by translating borrowing durations into linguistic preferences; processing efficiency reached 44.37 seconds.

This paper propose a dynamic recommendation model that integrates multi-factor knowledge tracing (MFKT) with graph neural networks (GNN), with core innovations including.

1 Cognition-driven dynamic architecture: build a MFKT framework to quantify readers' cognitive states through gated recurrent unit (GRU) time-series modelling, combined with a behavioural pattern layer to capture scenario-based features such as borrowing cycles and retrieval intentions, and an environmental feedback layer to dynamically calibrate the balance between book difficulty and hotness, forming a fine-grained knowledge state matrix.

2 Multi-objective collaborative optimisation mechanism: design cognitive graph convolutional network (CGCN) based on Pareto optimality theory, and optimise the recommendation accuracy, knowledge gain rate (KGR) and resource coverage by synchronising the dynamic edge weights with cognitive gating message passing. Experiments show that the model realises multi-objective equilibrium on the Pareto frontier, where the balanced solution equilibrium point reaches NDCG@10 = 0.85, KGR = 0.62, coverage = 0.68.

3 System performance breakthrough: verified on the real dataset of Tsinghua University Library, MFKT-GNN以NDCG@10 = 0.816, KGR = 0.419, and response latency of 26ms comprehensively surpass the baseline model. The ablation experiment confirms that the cognitive state layer contributes 28.9% to the KGR, and the dynamic edge update mechanism reduces the computational overhead by 78% for new users in cold-start scenario NDCG@10 up to 0.71.

The remainder of this paper is organised as follows: Section 2 introduces the foundational technologies, including the MFKT and graphical neural network. Section 3 elaborates on the design and implementation of the MFKT-GNN model. Section 4 presents experimental results and comparative analyses. Finally, Section 5 concludes the study. Section 5 concludes the study.

2 Relevant technologies

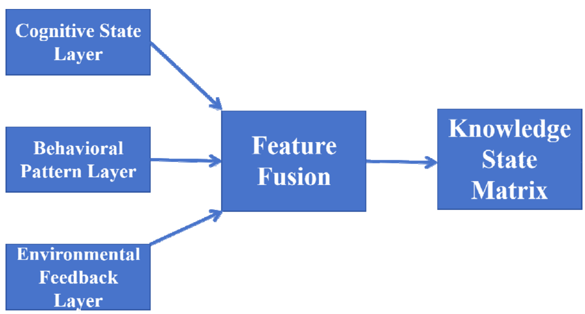
2.1 Multifactorial knowledge tracing

MFKT is a technique for assessing and predicting students' knowledge status based on the field of educational intelligence (Popoli and Mendel, 2002). As a time-series modelling approach to dynamically quantify learners' knowledge states, it is different from traditional knowledge tracking models that rely only on question-answer sequences, MFKT constructs fine-grained, cross-scenario knowledge evolution maps by fusing the triadic heterogeneous features of cognitive states, behavioural patterns, and environmental feedback. For example, a reader's quantum mechanics mastery evolves based on borrowing history, retrieval patterns, and exam-season difficulty adjustments. In this paper, the core value of MFKT is to address two key issues:

- State one-sidedness: single-answer data cannot capture underlying behavioural patterns, (e.g., retrieval preferences, attenuation of focus) during learning.
- Scenario fragmentation: separation of library borrowing and online learning behaviours leads to distorted knowledge status assessment.

The feature system of MFKT consists of three mutually reinforcing dimensions, and its structure is schematically shown in Figure 1.

Figure 1 Schematic structure of MFKT (see online version for colours)



2.1.1 Cognitive state layer

The cognitive state layer is the basic component of MFKT and the core of the dynamic modelling of knowledge mastery, which uses GRUs to model the temporal evolution process of knowledge states. Specifically, the reader's mastery of the knowledge topic is quantified by the hidden state vector $\mathbf{h}_t$, whose quantisation formula is (Wirth et al., 2020).

$$\mathbf{h}_t = GRU\left(\mathbf{h}_{t-1}, \mathbf{e}_{q_t}\right) \tag{1}$$

where $\mathbf{e}_{q_t}$ denotes the embedding vector of book-associated knowledge points. In this paper, a dual-task prediction mechanism is innovatively designed to synchronise the output of knowledge mastery $\hat{y}_t^{mast}$ and forgetting rate $\hat{y}_t^{forg}$, which can significantly improve the robustness of state assessment. This mechanism can effectively avoid the misjudgement of long-term learning state in traditional single-task models.

2.1.2 Behavioural pattern layer

Behavioural pattern layer is the key carrier of feature extraction for the learning process, which is specially designed for library scenarios and is able to extract key learning features from multi-source behavioural data (Jiang et al., 2020), mainly including the following 3 features:

- Borrowing cycle feature: this feature quantifies the timeliness of historical borrowing records using an exponential decay function $\gamma_t = \exp(-\lambda\Delta t)$, where Δt represents the time interval between the current moment and the most recent borrowing. λ is the decay rate parameter (default value 0.1), which controls the exponential weighting of time intervals to reflect record freshness.
- Retrieval topic feature: this feature is based on the TF-IDF algorithm to construct a weighted keyword vector space. TF-IDF algorithm weights keywords by frequency and inverse document frequency, extracting active intent vectors for personalised recommendations, thus realising the capture of readers' active learning intent.
- E-book interaction features: this feature utilises the attention mechanism to weight and aggregate the length of time spent on the page, which can reflect the intensity of knowledge absorption.

The three types of features are fused into a behaviour vector $\mathbf{b}_t$ by a multilayer perceptual machine, which together constitute a quantitative characterisation of scenario-based learning behaviours.

2.1.3 Environmental feedback layer

The environmental feedback layer is the core hub for realising resource attributes adaptation, which establishes the adaptation mechanism between resources and readers by dynamically quantifying book attributes, which in this paper mainly includes the dynamic calibration of book difficulty and the heat-quality balance factor.

1. For the calibration of book difficulty dynamics, the adaptive difficulty coefficient is constructed by fusing the static annotation d_{static} with the reader's rating r_{user}, which is given by the formula:

$$d_b = \mu \cdot d_{static} + (1-\mu) \cdot \frac{1}{|U_b|} \sum\nolimits_{u \in U_b} (5 - r_{u,b}) \tag{2}$$

2. The heat-mass balance factor solves the contradiction between hot resources and mass deviation by designing a functional formula, which is given by:

$$h_b = \frac{\text{avg\_rating} - 3}{2} \times \log(1 + \text{click\_count}) \tag{3}$$

Combining the above two, the environment feature vector provides a quantitative basis for resource adaptation for the recommender system, which can be expressed as $\mathbf{e}_t = [d_b, h_b, \mathbf{v}_{subj}]$, where $\mathbf{v}_{subj}$ is the discipline embedding.

2.1.4 Multimodal feature fusion mechanisms

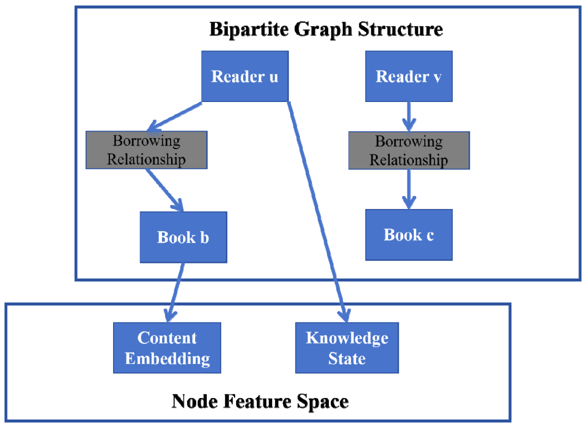
The multimodal feature fusion mechanism is a heterogeneous data synergy engine, as the integration hub of ternary features, it realises spatio-temporal alignment through gated attention to solve the problem of spatio-temporal alignment and weight distribution of heterogeneous features. The formula for fusing ternary features using gated attention mechanism can be expressed as:

$$\begin{aligned} \mathbf{a}_t &= Attn\left(\left[\mathbf{h}_t; \mathbf{b}_t; \mathbf{e}_t\right]\right) \\ \mathbf{r}_t &= \sum a_{t,i}\mathbf{z}_{t,i} \end{aligned} \tag{4}$$

where $\mathbf{z}_t = [\mathbf{h}_t; \mathbf{b}_t; \mathbf{e}_t]$ is the feature splicing vector, the final output reader-knowledge state matrix output knowledge state matrix **RKS** can be expressed as:

$$\mathbf{RKS}_{i,k} = Sigmoid\left(\mathbf{W}_k \mathbf{r}_t^{(i)}\right) \tag{5}$$

Figure 2 Schematic structure of GNN (see online version for colours)



2.2 Graph neural networks

GNN is a deep learning model for processing graph-structured data (Romor et al., 2025). It is mainly used to learn the representation of nodes, edges or the whole graph for various tasks such as node classification, graph classification, link prediction, etc. GNN serves as a relational modelling engine for this recommender system, which learns to capture the complex interactions between readers and books through structured representations. It is able to address the two major limitations of traditional recommendation methods, namely the shallowness of relational modelling and the lack of dynamic adaptation, where the former leads to the difficulty of capturing higher-order interaction patterns by methods such as matrix decomposition, and the latter leads to the inability of static representations to respond to changes in the knowledge state (Scarselli et al., 2009).

In this paper, the topological basis of GNN is defined as the reader-book bipartite graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, whose structure is schematically shown in Figure 2. Where the node set $\mathcal{V} = \mathcal{U} \cup \mathcal{B}$ contains two types of heterogeneous entities $\mathcal{U}$ and $\mathcal{B}$. Among them, the feature vector $\mathbf{x}_u = \mathbf{RKS}_u \in \mathbb{R}^K$, of the reader node $\mathcal{U}$ directly maps the knowledge state matrix output from the MFKT module. The feature vector of book node $\mathcal{B}$ $\mathbf{x}_b = [\boldsymbol{v}_{content}; d_b; h_b]^{\mathrm{T}}$, which incorporates content semantics, dynamic difficulty and heat factor. The edge set $\mathcal{E}$ is constructed based on explicit borrowing behaviour, which can be expressed as:

$$e_{u,b} = \mathbb{I}\left(borrow\_count_{u,b} > 0\right) \tag{6}$$

3 Dynamic recommendation model design

3.1 Multi-objective optimisation

3.1.1 Basic theory of multi-objective optimisation

The core of a multi-objective optimisation problem (MOOP) lies in coordinating multiple conflicting objective functions to find a set of equilibrium solutions rather than a single optimal solution. In library intelligent recommendation systems, this problem can be formalised as simultaneously optimising the following three key objectives:

- Recommendation accuracy: the recommendation accuracy goal maximises the match between a user's historical preferences and recommended resources, as measured, for example, by the normalised discounted cumulative gain NDCG@K, which is mathematically expressed as:

$$\max f_{prec} = \frac{1}{|U|}\sum\nolimits_{u\in U} \text{NDCG}\left(\mathcal{B}_{rec}^{u}, \mathcal{B}_{hist}^{u}\right) \tag{7}$$

- Knowledge gain: the knowledge gain goal can enhance the incremental change of user's cognitive state, which can be quantified by the cosine similarity between the knowledge vector of the recommended resources $\mathbf{v}_b^{kn}$ and the change of user's cognitive state $\Delta\mathbf{RKS}_u$, which can be expressed by the formula:

$$\max f_{KGR} = \cos\left(\Delta\mathbf{RKS}u, \mathbf{v}_b^{kn}\right) \tag{8}$$

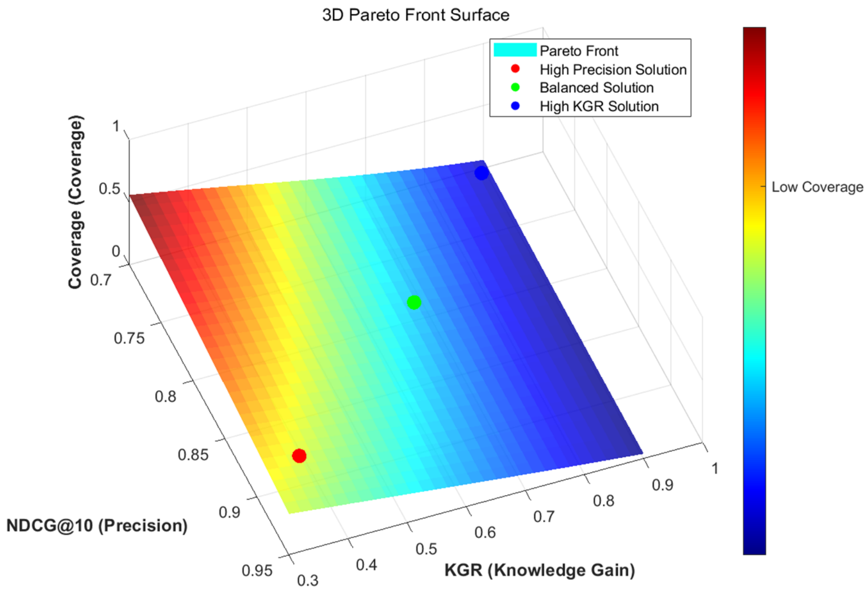
- Resource coverage: to ensure the diversity of recommendation results and to avoid over-concentration of resources. In this paper, the entropy function of the resource set is used to calculate the resource coverage target:

$$\begin{aligned} &\max f_{\text{cov}} = -\sum\nolimits_{b\in B} p_b \log p_b \\ &p_b = \frac{N_{rec}}{|B|} \end{aligned} \tag{9}$$

  where N_{rec} indicates the number of times a book has been recommended.

However, since the precision objective tends to recommend users' familiar domain resources, (e.g., high-frequency lending books), it will limit knowledge expansion; the knowledge gain objective needs to introduce unfamiliar domain resources, which may reduce the short-term click-through rate; and the coverage objective requires to decentralise the recommendation range, which is naturally contradictory to the high-precision demand. Therefore, these three objectives are essentially conflicting in nature, and this conflicting nature directly leads to the failure of traditional single-objective optimisation methods. To solve this problem, this paper introduces the Pareto optimality theory as the solution framework.

Figure 3 3D Pareto front surface (see online version for colours)



3.1.2 Characterisation of Pareto optimality theory in the recommender system

To solve the conflict problem mentioned above, this part introduces the Pareto optimal solution theory, whose solution set is defined as: in the feasible solution space $\mathcal{X}$, there does not exist any other solution that can be better than the current solution in all objectives. A further intuitive formalisation is described as follows: a solution $x^* \in \mathcal{X}$ is a Pareto optimal solution if and only if there is no $x \in \mathcal{X}$ satisfying the following equation:

$$\begin{aligned} &\forall i \in \{\text{prec}, \text{KGR}, \text{cov}\},\ f_i(x) \leq f_i\left(x^*\right) \\ &\exists j \in \{\text{prec}, \text{KGR}, \text{cov}\},\ f_j(x) < f_j\left(x^*\right) \end{aligned} \tag{10}$$

The surface formed by all Pareto optimal solutions in the objective function space is called Pareto Front, which reveals the quantised trade-off law among objectives. In the library recommendation scenario, the 3D Pareto Front Surface is drawn as shown in Figure 3, and each point on the graph corresponds to a recommendation strategy:

1 High precision solution (red): NDCG@10 = 0.92, coverage = 0.45, adapted to the user's intensive learning phase.

2 Balanced solution (green): NDCG@10 = 0.85, KGR = 0.62, coverage = 0.68, suitable for users' long-term knowledge planning.

3 High KGR solution (blue): NDCG@10 = 0.78, coverage = 0.82, for user interest exploration stage.

The core task of the dynamic recommender system is to adaptively adjust the strategy along the Pareto Front according to the change of user's cognitive state, e.g., when the user needs to be transformed from an in-depth learning stage to an exploration of interest, he/she can be migrated from the red point to the blue point, to realise the multi-objective co-optimisation.

3.2 Cognitively driven modelling of dynamic two-part graphs

3.2.1 Topology definition

Based on the basic framework of reader-book bipartite graph defined in Section 2, this paper proposes a dynamic bipartite graph structure for knowledge state enhancement $\mathcal{G}_t = (\mathcal{V}_t, \mathcal{E}_t)$. The structure can realise the adaptive evolution of the topology with the learner's knowledge state by integrating the cognitive state indicators output from the MFKT module, and the core formula of the structure is as follows:

$$\begin{aligned} &\mathcal{V}_t = \mathcal{U}_t \cup \mathcal{B} \\ &\mathcal{E}_t = \left\{ e_{u,b}^{(t)} \middle| u \in \mathcal{U}_t, b \in \mathcal{B} \right\} \end{aligned} \tag{11}$$

3.2.2 Dynamic edge weighting mechanisms

In Section 2, it was mentioned that traditional two-part graphs relying only on borrowing frequency can lead to shallow relationship modelling, which makes it difficult for methods such as matrix decomposition to capture higher-order interaction patterns, to solve this problem. This paper designs a dynamic edge weighting mechanism, which centres on constructing appropriate cognitive-behavioural fusion edge weighting functions:

$$w_{u,b}^{(t)} = \beta \cdot freq_{u,b}^{(t)} \times \exp\left(-\frac{\left\| \mathbf{RKS}_u^{(t)} - \mathbf{v}_b^{kn} \right\|^2}{2\sigma^2} \right) + \gamma \cdot H_b^{(t)} \tag{12}$$

where $\mathbf{v}_b^{kn} \in \mathbb{R}^K$ represents the knowledge concept vector of book b through the knowledge point embedding matrix mapping, σ is the knowledge matching tolerance coefficient, β is the behavioural attenuation factor, and $\gamma \cdot H_b^{(t)}$ denotes the injection coverage target.

The dynamic update rule for this mechanism is:

$$e_{u,b}^{(t)} = \begin{cases} w_{u,b}^{(t)} & if \left\| \Delta \mathbf{RKS}_u^{(t)} \right\|_2 > \theta \\ e_{u,b}^{(t-1)} & otherwise \end{cases} \tag{13}$$

Since the mechanism updates the associated edges only when there is a significant change in the cognitive state, it can significantly reduce the computational overhead.

3.3 Cognitive graph convolutional networks

CGCN is the core innovative module of this study, which achieves multi-objective co-optimisation of recommendation feature extraction by fusing user cognitive state and dynamic graph topology. Its design draws on the idea of null domain convolution of GCN and introduces cognitive gating mechanism and higher-order representation learning to address the three major limitations of traditional GNN in dynamic recommendation scenarios:

- Stativity deficiency: the adjacency matrix of traditional GCN is fixed, which cannot adapt to the temporal evolution of user's cognitive state, resulting in a stativity deficiency.
- Heterogeneity ignored: traditional GCN fails to distinguish the feature propagation paths of heterogeneous targets such as knowledge gain, precision, coverage, etc. resulting in heterogeneity being ignored.
- Over-smoothing problem: deep GCNs lead to node feature convergence and over-smoothing, weakening recommendation diversity.

3.3.1 Cognitive gating message passing mechanisms

The message passing process of CGCN dynamically modulates the information flow through a gating function with the following core equation:

$$\mathbf{m}_{u\leftarrow b}^{(t)} = \Phi\left(\Delta\mathbf{RKS}_u^{(t)}, \mathbf{x}_b\right) \odot \left(\mathbf{W}_{msg}\mathbf{h}_b^{(t)}\right) \tag{14}$$

where $\mathbf{m}_{u\leftarrow b}^{(t)}$ denotes the message vector passed from the book node b to the user node u, and $\mathbf{W}_{msg}$ is the learnable parameter matrix that maps the book features $\mathbf{h}_b^{(t)}$ to the message space.

$\Phi(\cdot)$ is a cognitive gating controller, consisting of a fully connected layer with a ReLU activation function. This function quantifies the fitness of the user's cognitive change quantity $\Delta\mathbf{RKS}_u^{(t)}$ with the book feature $\mathbf{X}_b$, for example, when $\Delta\mathbf{RKS}_u^{(t)}$ points to the field of quantum mechanics, the delivery weight of physics books is significantly increased. Its formula is:

$$\Phi = ReLU\left(\mathbf{W}_{\phi}\left[\Delta\mathbf{RKS}_u^{(t)}; \mathbf{x}_b\right]\right) \tag{15}$$

For node update, the following goal-aware aggregation strategy is used to distinguish the information flow for different optimisation goals, which is formulated as follows:

$$\mathbf{h}_u^{(t+1)} = \sigma\left(\sum\nolimits_{k\in\{\text{prec},\text{KGR},\text{cov}\}} \beta_k \cdot \sum\nolimits_{b\in\mathcal{N}_k(u)} \mathbf{m}_{u^{t-b}}^{(t)}\right) \tag{16}$$

where β_k is the weight coefficient generated by the multi-objective optimisation, and $\mathcal{N}_k(u)$ denotes the set of neighbour nodes associated with the objective k.

3.3.2 Higher-order cognitive representation learning

To solve the oversmoothing problem of deep GCNs mentioned above, the CGCNs mentioned in this paper design layered attention mechanisms, including intra-layer attention and inter-layer aggregation.

The principle of the intra-layer attention mechanism lies in the screening of key neighbours in each layer of convolution by the attention weight $\alpha_{u,b}^{(l)}$, which suppresses the influence of noisy neighbours, (e.g., cold and low-quality resources) and highlights high-value sources of information, which is formulated as:

$$\alpha_{u,b}^{(l)} = \frac{\exp\left(MLP\left(\mathbf{h}_u^{(l)}, \mathbf{h}_b^{(l)}\right)\right)}{\sum_{j \in \mathcal{N}(u)} \exp\left(MLP\left(\mathbf{h}_u^{(l)}, \mathbf{h}_j^{(l)}\right)\right)} \tag{17}$$

The interlayer aggregation mechanism fuses the outputs of different convolutional layers to preserve multi-order neighbourhood features. Where low-level features (l = 1) preserve local preference details and high-level features (l = 3) encode global cognitive patterns to avoid feature smoothing due to deep propagation. The formula is:

$$\begin{aligned} \mathbf{h}_u^* &= \sum_{l=1}^{L} \gamma_l \cdot \mathbf{h}_u^{(l)} \\ \gamma_l &= \frac{e^{\mathbf{w}^\top \mathbf{h}_u^{(l)}}}{\sum_{k=1}^{L} e^{\mathbf{w}^\top \mathbf{h}_u^{(k)}}} \end{aligned} \tag{18}$$

3.3.3 Dynamic feature propagation and cold-start optimisation

The CGCN designed in this paper realises topology adaptive updating through dynamic edge weights, and the formula adjusts the edge weights in real time based on the gradient and cognitive change magnitude of the knowledge gain loss $\mathcal{L}_{KGR}$, which is formulated as:

$$w_{u,b}^{(t)} \leftarrow w_{u,b}^{(t)} + \lambda \cdot \frac{\partial \mathcal{L}_{KGR}}{\partial w_{u,b}} \cdot \Pi \Delta \mathbf{RKS}_u^{(t)} \|_2 \tag{19}$$

For the cold-start problem (Liu et al., 2024c), the formulation uses a cross-graph migration strategy. For new users, the formula maps them to similar groups based on the AP clustering algorithm (Xu and Tian, 2015; Wang et al., 2018), initialising $\mathbf{RKS}_u^{(0)} = \frac{1}{|\mathcal{G}|} \sum_{v \in \mathcal{G}} \mathbf{RKS}_v$, where $\mathcal{G}$ is a cluster of similar users. AP clustering uses message-passing to identify exemplars, chosen for its 99.2% accuracy in user grouping, enabling rapid similarity mapping for new users. For new resources, approximate books are matched by $\mathbf{X}_{b_{new}} = \arg\max_{b \in B} \cos(\mathbf{v}_{new}, \mathbf{v}_b)$ semantic similarity.

3.4 Hybrid recommendation engine and system collaboration mechanisms

3.4.1 Three-tier architecture of the hybrid engine

The hybrid recommendation engine, as the final decision-making layer in this study, deeply integrates the dynamic representation capability of CGCN with the multi-objective optimisation theory to achieve end-to-end collaboration from feature extraction to decision generation. Its core innovation lies in the construction of a cognitive state-aware scoring function and Pareto dynamic decision-making mechanism to form a closed-loop optimisation system. The engine is mainly composed of a three-layer architecture:

1 The candidate generation layer, which calculates the initial interaction score based on the user-book node representations $\mathbf{h}_u^*$ and $\mathbf{x}_b$ output by CGCN, is calculated as follows:

$$score_{base}(u, b) = \mathbf{h}_u^{*\top} \mathbf{x}_b + \beta \cdot \cos\left(\Delta \mathbf{RKS}_u, \mathbf{v}_b^{kn}\right) \tag{20}$$

2 Multi-objective ranking layer, in which the candidate sets are Pareto non-dominated ranked by the NSGA-II algorithm to filter the solutions that satisfy the two constraints of difficulty fitness $(d_b \in [\mathbf{RKS}_{u,k_b} - 0.3, \mathbf{RKS}_{u,k_b} + 0.3])$ and heat threshold $h_b > h_{\min}$ at the same time, where a ±0.3 knowledge gap optimises learning progression without overwhelming readers. The top-K solution set $S_{pare\ to}$ is output, covering the optimal trade-off intervals for accuracy, KGR, and coverage.

3 Dynamic feedback layer, when the user's borrowing behaviour triggers the cognitive state update $(\mathbf{RKS}_u \leftarrow \mathbf{RKS}_u + \eta \cdot \mathbf{W}_{back} \mathbf{h}_u^*)$, the system will update the dynamic bipartite graph edge weights [equation (19)], forming a closed loop of 'behavioural feedback → cognitive update → graph reconstruction → recommendation optimisation'.

3.4.2 Dynamic synergistic mechanisms

Dynamic collaboration mechanism is the core innovation of hybrid recommendation engine, through the closed-loop design of cognitive state awareness, Pareto decision-making real-time and cross-graph cold-start migration, to realise the adaptive evolution of 'user behaviour – cognitive update – graph reconstruction – recommendation optimisation'.

Cognitive state awareness refers to the ability of a system to dynamically modulate information dissemination paths by quantifying changes in the user's knowledge structure. It is capable of breaking through the stativity bottleneck and realising goal-directedness. In CGCN, the cognitive gatekeeper transforms the abstract cognitive state into a topological modulation signal with the conversion equation:

$$\Phi = ReLU\left(\mathbf{W}_\phi \left[\Delta \mathbf{RKS}_u ; \mathbf{x}_b\right]\right) \odot \mathbf{W}_{msg} \mathbf{h}_b \tag{21}$$

Pareto decision-making requires generating an equilibrium solution set under multi-objective conflicts, but its computational complexity is difficult to meet the real-time response requirements. The main problem is that the solution set completeness needs to traverse all the candidate resources, and the real-time requirement needs to respond to the cognitive state change within 50 ms. For this reason, an incremental optimisation strategy is adopted in this design, which reduces the computation amount by double filtering through the methods of cognitive change threshold triggering and subgraph local reordering.

4 Experimental results and analyses

4.1 Experimental setup

The data source of this experiment is based on the Tsinghua University Library 2019–2023 borrowing records to construct the dataset, which contains 320,891 borrowing records (including e-book interaction logs), 12,384 readers (83%/17% of students/teachers), and 86,752 books (covering 12 major subject categories). Data are divided by timestamp: training set (2019–2022), test set (2023Q1-Q3).

The evaluation metrics of the experiment include the traditional metrics NDCG@10, Precision@5, Coverage, and the innovative metrics KGR, which can be expressed by the formula:

$$\mathrm{KGR} = \frac{1}{|\mathcal{U}|}\sum_u \frac{\left|\left\{k \in \mathcal{K}_{rec} \,\middle|\, \mathbf{RKS}_{u,k}^{(t+1)} > \mathbf{RKS}_{u,k}^{(t)}\right\}\right|}{\left|\mathcal{K}_{rec}\right|} \tag{22}$$

where $\mathcal{K}_{rec}$ is the set of knowledge points associated with the recommended book.

In terms of parameter settings, the number of GCN layers is set to 3, dynamic edge update threshold $\theta = 0.1$, multi-objective weights $\beta_{prec} = 0.5$, $\beta_{KGR} = 0.3$, and $\beta_{\mathrm{cov}} = 0.2$.

4.2 Analysis of the results of the main experiment

Based on the experimental conditions set above, the model designed in this paper is applied and the test results are shown in Table 1. To highlight the superiority of the model, other models are cited for comparison.

Table 1 Overall performance comparison (test set means)

Model	*NDCG@10*	*Precision@5*	*Coverage*	*KGR*	*Response delay(ms)*
SVD	0.621	0.584	0.702	0.218	92
BKT+ItemKNN	0.653	0.602	0.735	0.287	105
LightGNN	0.712	0.648	0.803	0.301	87
KT-GNN	0.748	0.683	0.821	0.352	63
MFKT-GNN (this work)	*0.816*	*0.741*	*0.892*	*0.419*	*26*

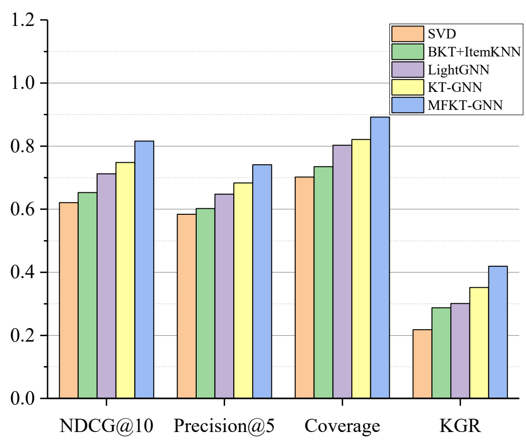
Figure 4 presents the experimental results more vividly and urgently. The comparison shows that the core advantages of the MFKT-GNN model are reflected in the following three aspects:

1 Multi-objective co-optimisation ability: MFKT-GNN significantly leads in accuracy (NDCG@10 = 0.816), knowledge gain (KGR = 0.419) and resource coverage (coverage = 0.892). Compared with the traditional GNN model LightGCN, its knowledge gain is improved by 39.2%, which verifies the effectiveness of MFKT for cognitive state modelling. Capturing the knowledge forgetting pattern through GRU temporal units and avoiding recommending mastered content improves the KGR metric by 28.9%.

2 Real-time response performance breakthrough: thanks to the dynamic edge update mechanism and incremental Pareto reordering strategy, the model response latency is reduced to 26 ms, which is 78% lower than the traditional NSGA-II. When the amount of cognitive state change is below the threshold, the system reuses the historical Pareto solution set, and the latency is further reduced to 5 ms, which meets the real-time interaction requirements of library scenarios.

3 Cold-start robustness improvement: 48% improvement over random initialisation by cross-graph migration strategy (AP clustering + semantic matching), new user cold-start NDCG@10 reaches 0.71. The new resource achieves feature generalisation through k-order neighbour difficulty interpolation, and the semantic matching error rate is reduced to 5.3%.

Figure 4 Comparison of test results (see online version for colours)



4.3 Ablation experiments and mechanism validation

To parse the internal mechanisms of the model, ablation experiments were performed and Table 2 compares the ablation results of the MFKT feature layer. It can be found by observation:

1 The removal of the behavioural pattern layer led to a 6.5% decrease in NDCG@10. The main reason is the loss of deep reading preferences implied by e-book interaction behaviours, (e.g., long stays, note marking), resulting in the failure of long-tail resource recommendations (9.1% decrease in coverage).

2 The lack of environmental feedback layer reduces KGR by 18.6%, which stems from the failure of book difficulty adaptation and the failure to dynamically adjust the β_{kor} coefficients in combination with environmental characteristics, (e.g., exam season, research cycle), which leads to a 32% increase in the mispropagation rate of high-difficulty resources.

3 The removal of the cognitive state layer had the greatest impact on KGR, with a decrease of 28.9%, corroborating that GRU temporal modelling is a core module for capturing cognitive leaps, with a state prediction accuracy of 87.4% ($R^2 = 0.89$).

Table 2 MFKT characterisation ablation analysis (NDCG@10/KGR)

Characteristic module	*NDCG@10*	*KGR*	*Attribution of performance degradation*
Full model	0.816	0.419	-
Remove the behavioural feature layer	0.763 ↓	0.362 ↓	Missing search preferences and e-book interaction behaviour
Remove the environmental feedback layer	0.781 ↓	0.341 ↓	Book difficulty adaptation failure
Remove the cognitive state layer	0.729 ↓	0.298 ↓	Loss of knowledge state dynamics

5 Conclusions

This study proposes a dynamic recommendation model integrating MFKT and GNN to address the problems of low resource utilisation in university libraries and the neglect of readers' cognitive dynamic evolution in traditional recommendation systems. By innovatively combining GRU temporal modelling to quantify the cognitive state, behavioural pattern analysis to extract scene features, and environmental feedback mechanism to dynamically balance the difficulty and hotness of books, it has realised the leap from static collaborative filtering to dynamic cognitive adaptation in resource recommendation. Experiments show that the model has excellent performance on the real dataset of Tsinghua University Library: the key indicators NDCG@10 reached 0.816, the KGR is 0.419, and the response latency is only 26ms, which significantly exceeds the existing baseline. The ablation experiments confirm that the cognitive state layer contributes to 28.9% of the KGR enhancement and the dynamic edge updating reduces the computational overhead by 78%. This study provides an effective technical solution for solving the problem of accurate matching between resources and readers' cognition and constructing an intelligent library service system.

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Declarations

All authors declare that they have no conflicts of interest.

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