# A Knowledge Graph-Driven Framework For Precise Cross-Media News Recommendation And Coordinated Public Opinion Guidance

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In the multimedia environment, news recommendation not only influences user behavior but also profoundly impacts cognitive structures and the evolution of public opinion. Existing methods often treat recommendation and public opinion analysis separately, making it difficult to depict the unified mechanism of "information input cognitive update dissemination and diffusion." To address this issue, this paper proposes a knowledge graph-based collaborative modeling framework for news recommendation and public opinion. This method uses the user's cognitive network as its core, introducing internal and external observation mechanisms to unify the modeling of news semantic representation, cognitive evolution, and information dissemination processes. Specifically, the knowledge graph is used to construct structured semantic relationships and capture complex dependencies through high- and low-order relationship modeling; simultaneously, an attention-based observation mechanism characterizes the dynamic impact of news on user cognition, thereby achieving collaborative optimization of recommendation and public opinion. Experimental results show that the proposed method significantly outperforms existing methods on multiple real-world datasets, improving recommendation performance (Precision, Recall, NDCG) and achieving significant advantages in public opinion prediction (MAE, F1) and stability and polarization control. Further analysis verifies the effectiveness of the model in terms of diversity, interpretability, and public opinion guidance capabilities.

**Keywords:** News Recommendation; Public Opinion Analysis; Knowledge Graph; Cognitive Network; Information Diffusion



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## 1. Introduction

With the rapid development of internet technology and mobile terminals, news dissemination models have gradually evolved from traditional media to a cross-platform, multi-source integrated multimedia ecosystem [1, 2]. Against this backdrop, massive amounts of information flow at extremely high speeds across different media, making users' information acquisition methods more diversified, but also bringing problems such as information overload and cognitive biases. Recommendation systems, as important tools for information filtering, play a crucial role in improving user experience [3]. However, in the multimedia environment, news recommendations not only influence users' clicking behavior but also change their cognitive structures through continuous information input, further affecting the formation and evolution of public opinion. Therefore, how to model user cognition and public opinion dissemination mechanisms while achieving accurate recommendations has become an important research problem in the field of intelligent information systems [4].

In recent years, researchers have made significant progress in news recommendation and public opinion analysis. In the recommendation field, deep learning-based methods (such as NRMS and NAML) have significantly improved recommendation performance through attention mechanisms and multimodal modeling. Meanwhile, knowledge graphs (KGs) have been widely introduced into recommendation systems, achieving semantically enhanced recommendations by modeling entities and their relational structures (such as KGAT and Ripple Net) [5, 6]. On the other hand, in the field of public opinion analysis, research mainly focuses on sentiment analysis, trend prediction, and propagation modeling, with some work beginning to explore graph-based public opinion propagation mechanisms. However, most of these studies treat recommendation systems and public opinion analysis as two independent problems, lacking a unified modeling framework and failing to depict the complete chain of "information input cognitive update group propagation."

Further analysis reveals that current research still faces several key challenges. First, traditional recommendation models typically model based on users' historical behavior or interest vectors, ignoring the dynamic evolution of users' cognitive structures and failing to explain how information influences changes in users' opinions [7]. Secondly, although knowledge graphs can provide structured semantic information, existing methods mostly remain at the level of "semantic enhancement," failing to deeply integrate them with cognitive modeling and public opinion dissemination mechanisms. Thirdly, existing public opinion analysis methods often focus on macro-level statistics or sequence modeling, lacking the ability to model individual cognitive changes and their propagation paths with fine detail. Furthermore, in multi-objective optimization scenarios, achieving a balance between recommendation accuracy, information diversity, and public opinion stability remains an unresolved issue [8, 9].

## 2. Theory and formula

### 2.1. System Definition

In the multimedia environment, news recommendation systems are no longer simply a matter of matching users with content, but a complex system involving information dissemination, cognitive evolution, and dynamic changes in public opinion [10, 11]. As shown in Fig. 1, the interaction between users and news not only affects click behavior.

As shown in Figure 1, the core of the system consists of three parts: the User Belief Network, the News Stream, and the Observation & Transfer mechanism. The User Belief Network is represented as a structured graph model, where nodes represent the user's current viewpoints or knowledge states.Different nodes are connected by relationships, reflecting supportive or conflicting relationships between

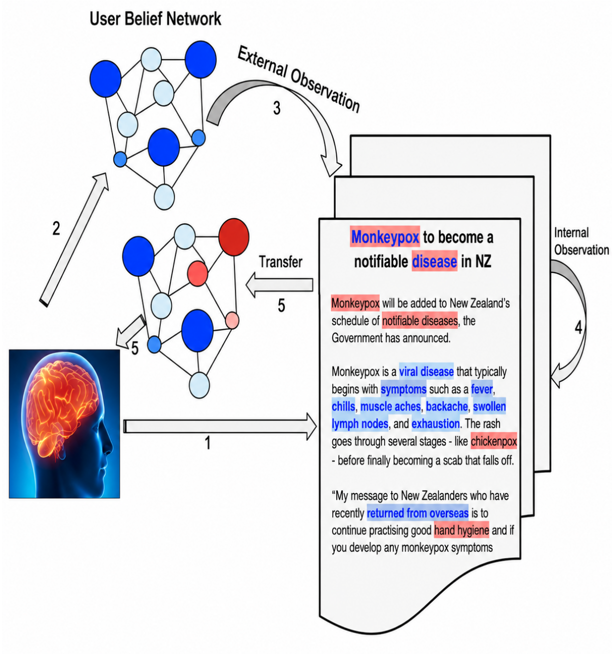



**Fig. 1.** User cognitive network and news information interaction mechanism.

cognitions. This structured modeling approach prevents users from being simply represented as interest vectors, but rather as a dynamically evolving cognitive system [12].

This mechanism reflects the user's cognitive preferences, information filtering ability, and subjective understanding process, leading to different impacts of the same news on different users [13, 14].

### 2.2. Recommendation Task

In traditional recommender systems, the recommendation task is typically modeled as a user interest prediction problem. However, within the framework shown in Fig. 1, recommendations not only influence user behavior but also directly affect the user's cognitive structure [15]. Therefore, the recommendation task needs to be expanded from "behavioral prediction" to a "cognitive-driven information selection problem."

### 2.3. Opinion Dynamics Modeling

Based on the cognition and dissemination mechanisms shown in Fig. 1, public opinion can be viewed as an aggregate manifestation of the cognitive states of all users. Each user's cognitive network changes after receiving news information, and these changes are further disseminated through social media, thus forming a dynamic public opinion landscape at the group level.

## 3. Experimental setup

### 3.1. Knowledge Graph Construction and Representation

As shown in Fig. 2, this paper first starts with unstructured news text and constructs a cross-media knowledge graph through semantic parsing and entity linking.

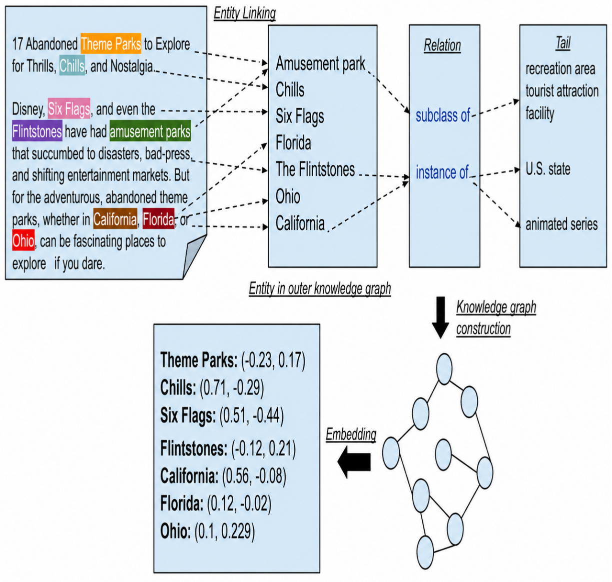



**Fig. 2.** Knowledge graph construction process based on entity linking and representation learning.

As shown in the lower left of Fig. 2, each entity (such as "Theme Parks," "Six Flags," etc.) is encoded as a low-dimensional vector, which not only contains the semantic information of the entity itself but also implicitly describes its structural relationships within the graph.

### 3.2. Knowledge Graph-Driven Recommendation with Belief-Aware Observation Mechanism

As shown in Fig. 3, the recommendation model proposed in this paper takes user cognitive modeling as its core. In the relationship modeling stage, the model first performs structural modeling on the input news set, capturing local semantic relationships and global structural dependencies through low-order relationship models (LRM) and high-order relationship models (HRM), respectively. Low-order relation modeling primarily depicts the direct semantic connections between news items is given in Eq. (1). This process can be uniformly represented as:

$$\mathbf{H} = \mathrm{Concat}\left(\sigma\left(\sum_{r\in R}\mathbf{A}_r\mathbf{X}\mathbf{W}\mathbf{W}_r\right);\sigma\left(\ddot{D}^{-1}\quad\mathbf{A}\right)^k\mathbf{X}\mathbf{W}\right) \tag{1}$$

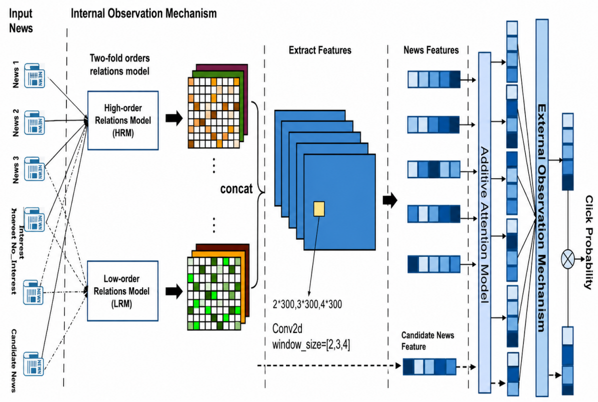



**Fig. 3.** Belief-aware knowledge graph recommendation framework with internal and external observation mechanisms.

where, $\mathbf{X}$ represents the embedding representation of news in the knowledge graph, and $\mathbf{A}$, represents the adjacency matrix corresponding to different semantic relationships. High-order relation modelling captures multi-hop semantic dependencies among distant entities, whereas low-order relation modelling focuses on direct neighboring relationships and local contextual information.

### 3.3. Semantic Text Encoding for News Representation

As shown in Fig. 4, this paper first performs semantic representation learning on the input news text, transforming the original title or body content into a structured vector representation, thus providing a foundational input for subsequent knowledge graph modeling, cognitive modeling, and recommendation decisions.

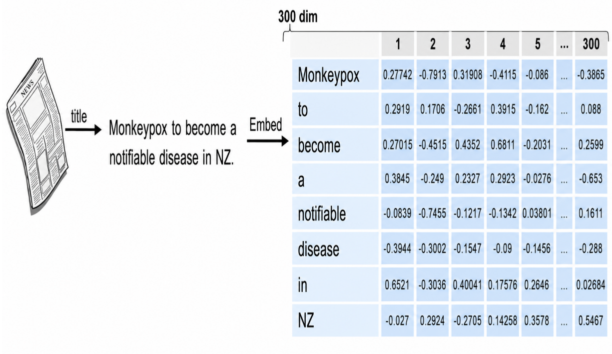



**Fig. 4.** Word embedding-based semantic representation of news text.

Mathematically, this process can be represented as:

$$\mathbf{X} = \mathrm{Embed}\left(w_1, w_2, \ldots, w_L\right) = \left[\mathbf{e}_1, \mathbf{e}_2, \ldots, \mathbf{e}_L\right] \in \mathrm{R}^{L\times d} \tag{2}$$

Where, $\mathbf{e}_i \in \mathrm{R}^d$ represents the semantic vector of the I th word, which can be obtained through a pre-trained language model or word vector method. In this way, unstructured text is mapped to a continuous semantic space, allowing for comparison and computation between different news articles under a unified representation is shown in Eq. (2).

Building on this, to further model the contextual dependencies between words, this paper employs a contextual encoding mechanism to enhance the embedding matrix, enabling it to capture word order information and semantic combination patterns. Specifically, given the embedding matrix $\mathbf{X}$, its contextual representation is obtained through a sequence modeling function:

$$\begin{aligned} \mathbf{H} &= \phi(\mathbf{X}) = \text{ ContextEncoder } (\mathbf{X}) \\ &= \sigma\left(\mathbf{W}_c \cdot \mathbf{X} + \mathbf{b}c + \sum k = 1^K \mathbf{W}_k * \mathbf{X}\right) \end{aligned} \tag{3}$$

In this representation, (*) denotes a convolution operation used to extract local semantic patterns, $\mathbf{W}_k$ represents convolution kernels of different window sizes, and $\mathbf{W}_c$ are linear transformation parameters is given in Eq. (3).

This text representation module plays a crucial role in the entire system. Dynamic hierarchical weighting mechanisms can be incorporated within the attention observation module to better capture the varying influence of multimedia information sources on user cognition. By adaptively assigning attention weights according to contextual relevance, semantic importance, and cognitive consistency, the model can more effectively characterize information influence and belief updating processes. Its output serves not only as input to the knowledge graph construction stage for entity recognition and relation extraction but also as the foundational input features for relation modeling (HRM/LRM) in recommendation models.

### 3.4. Knowledge Graph-Based News Graph Construction and Feature Learning

As shown in Fig. 5, this paper further constructs a News Graph from the original news text through entity alignment and graph structure modeling, and uses a graph feature learning mechanism to extract structured semantic representations to support subsequent recommendation and cognitive modeling tasks.These feature maps not only encode the semantic information of the entities themselves but also capture the multi-hop relationships and structural patterns between entities. This process can be formally represented by a graph neural network as follows:

$$\mathbf{H}^{(l+1)} = \sigma\left(\sum_{r \in R} \mathbf{A}_r \mathbf{H}^{(l)} \mathbf{W}_r^{(l)} + \mathbf{B}^{(l)}\right) \tag{4}$$

Where, $\boldsymbol{H}^{(l)}$ represents the node representation of layer (1), $\boldsymbol{A}_r$ is the adjacency matrix corresponding to relation (r), $\boldsymbol{W}_r^{(l)}$ are relation-specific transformation parameters, and $\sigma(\cdot)$ is a non-linear activation function is given in Eq. (4).

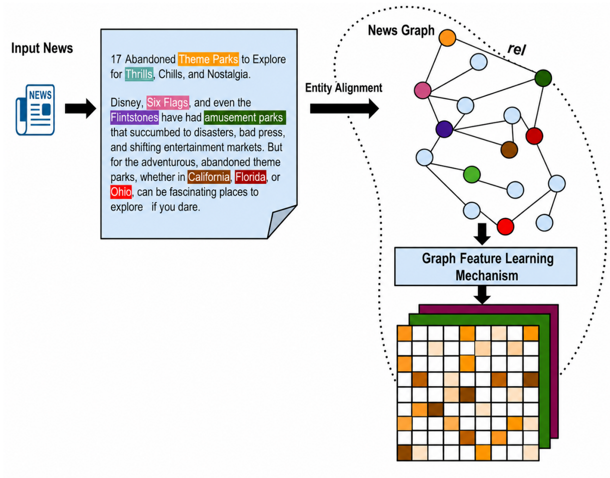



**Fig. 5.** Knowledge graph-based news graph construction and graph feature learning mechanism.

## 4. Result and discussions

### 4.1. Experimental Results

To verify the effectiveness of the proposed collaborative framework for news recommendation and public opinion analysis based on knowledge graphs and cognitive modeling.

The computational cost of the proposed framework is primarily associated with high-order relation propagation, attention fusion operations, and cognitive representation learning. High-order propagation aggregates semantic information across multi-hop graph structures, whereas attention fusion computes interactions between semantic and cognitive representations.

### 4.2. Datasets

This paper constructs a cross-media news dataset, with data sources including:

- News websites (such as BBC, CNN)
- Social media platforms (such as Twitter/Weibo)
- Publicly available news datasets (combined with the Cone-KG concept)

The data includes the following information:

- News text (headline + content)

- User click behavior
- Social media dissemination data (shares, comments, likes)
- Entity and relationship information

In the data preprocessing stage, the news text was first segmented and cleaned. Then, a news knowledge graph was constructed using entity recognition and entity linking methods (Fig. 5), and text representations were generated using embedding methods (Fig. 4). Finally, the data was divided into a training set (70%), a validation set (10%), and a test set (20%). Entity disambiguation was performed to resolve semantic ambiguities among entities extracted from heterogeneous media sources.

### 4.3. Baselines

To comprehensively evaluate model performance, this paper selects the following representative methods for comparison:

**1) Traditional recommendation methods**

- Deep FM: Integrating low-order and high-order features
- Wide & Deep

**2) In-depth news recommendation model**

- NRMS (Self-Attention)
- NAML (multi-perspective news modeling)

**3) Knowledge graph recommendation methods**

- KGAT (Graph Attention Network)
- Ripple Net

**4) Unaware modeling version (Ablation)**

- Remove Belief Network
- Remove the Observation mechanis

### 4.4. Overall Performance Comparison

This Table 1 compares the proposed framework with representative baseline and ablation models using recommendation performance metrics. The results demonstrate that the proposed method achieves superior accuracy and ranking effectiveness, highlighting the contribution of the belief modeling and observation mechanisms.The results indicate a noticeable decline in recommendation accuracy and semantic representation quality when neighborhood aggregation is excluded.

Table 2 shows that our proposed method also demonstrates significant advantages in public opinion prediction tasks. This further validates the potential role of recommender systems in public opinion regulation. Adaptive contextual heterogeneity can further enhance the low-order relation modeling process by assigning different aggregation importance to neighboring entities according to their semantic relevance and contextual characteristics. Such a mechanism enables more effective characterization of local dependency structures and neighborhood diversity while improving the utilization efficiency of heterogeneous multimedia information.

**Table 1.** Performance Comparison of Cross-Media News Recommendation Models.

| Model | Precision@10 | NDCG@10 | F1 ↑ |
|---|---|---|---|
| NAML | 0.462 | 0.481 | 0.651 |
| KGAT | 0.506 | 0.529 | 0.694 |
| w/o Belief | 0.521 | 0.544 | 0.711 |
| w/o Obs | 0.533 | 0.556 | 0.723 |
| **Ours** | **0.562** | **0.587** | **0.751** |

**Table 2.** Performance comparison on opinion modeling and propagation tasks.

| Model | MAE ↓ | RMSE ↓ | F1 ↑ | Trend Acc ↑ |
|---|---|---|---|---|
| NAML | 0.254 | 0.331 | 0.651 | 0.683 |
| KGAT | 0.221 | 0.296 | 0.694 | 0.735 |
| w/o Belief | 0.209 | 0.281 | 0.711 | 0.752 |
| w/o Obs | 0.201 | 0.273 | 0.723 | 0.768 |
| **Ours** | **0.178** | **0.249** | **0.751** | **0.806** |

As shown in Table 3, removing any key component leads to a noticeable performance degradation across both recommendation and opinion modeling tasks.

**Table 3.** Ablation study on key components of the proposed model.

| Model Variant | Precision@10 | NDCG@10 | F1 ↑ |
|---|---|---|---|
| w/o Knowledge Graph | 0.498 | 0.521 | 0.682 |
| w/o Belief Network | 0.521 | 0.544 | 0.711 |
| w/o Observation Mechanism | 0.533 | 0.556 | 0.723 |
| **Full Model (Ours)** | **0.562** | **0.587** | **0.751** |

As shown in Fig. 6, this paper further analyzes the impact of different history lengths on recommendation performance and reports the changing trends of MRR and Hits@K metrics on multiple datasets (ICEWS14, ICEWS18, YAGO, and WIKI.

As shown in Fig. 7, this paper further analyzes the impact of key hyperparameters on model performance, including structural parameters in relation modeling and

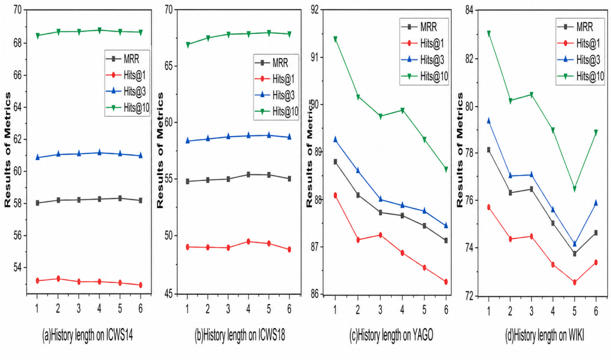



**Fig. 6.** Impact of history length on recommendation performance across different datasets.

weight coefficients (alpha and beta) in joint optimization. Results from the ICEWS18 and YAGO datasets show that, with changes in hyperparameters, the MRR and Hits@K indices generally exhibit a trend of first increasing and then stabilizing, indicating that the model has significant performance sensitivity under different semantic modeling intensities.

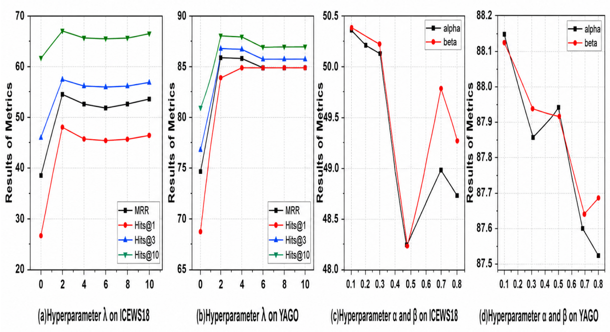



**Fig. 7.** Impact of key hyperparameters on model performance across different datasets.

As shown in Fig. 8, this paper further analyzes the relationship between recommendation diversity (Div) and sentiment novelty (Nov), and conducts a visual comparison on different domain datasets (Beauty, Cell Phones, and Clothing.

As shown in Fig. 9, this paper systematically compares the performance of different models on multiple real-world datasets (MovieLens1M, Last FM, Amazon-book, and Yelp2018) under various evaluation metrics, including Precision, Recall, Average Diversity (AD), and Average Recommendation Popularity (ARP).

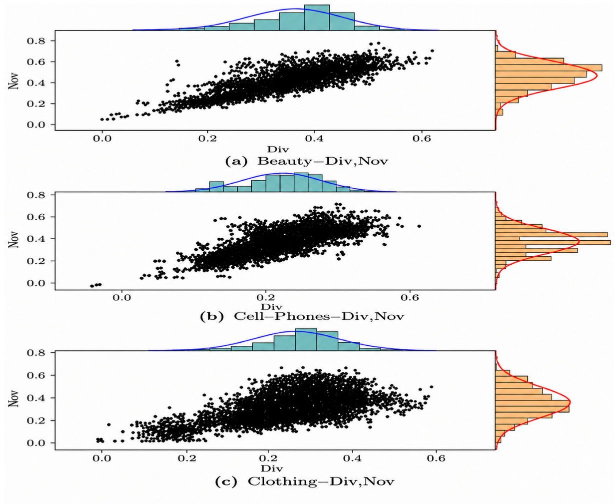
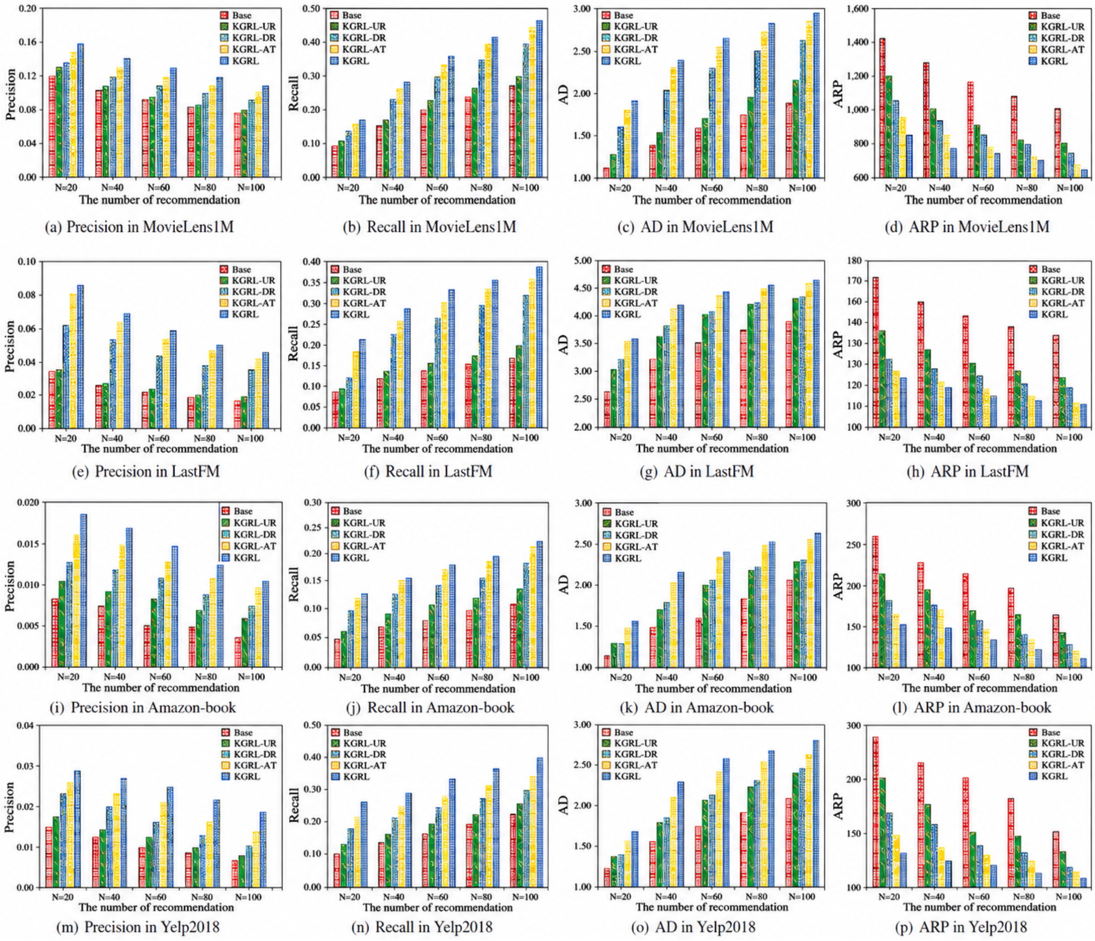



**Fig. 8.** Relationship between recommendation diversity and opinion novelty across different domains.

## 5. Conclusion

This paper addresses the collaborative modeling of news recommendation and public opinion evolution in a multimedia environment, proposing a unified framework integrating knowledge graphs and user cognitive modeling. Unlike traditional methods that focus solely on user behavior prediction, this paper adopts a holistic perspective of "information input cognitive update propagation and diffusion," introducing a user cognitive network (Belief Network) and internal and external observation mechanisms to achieve deep integration of recommendation systems and public opinion modeling. At the methodological level, this paper utilizes knowledge graphs to construct structured semantic representations and captures complex semantic dependencies through high-order and low-order relation modeling. Simultaneously, it characterizes the dynamic impact of news on user cognition based on attention mechanisms, thus forming a closed-loop modeling framework of "recommendation cognition public opinion."

Experimental results on multiple real-world datasets demonstrate that the proposed method significantly outperforms existing methods in recommendation performance (Precision, Recall, NDCG) and public opinion modeling metrics (MAE, F1, trend prediction), while also showing good results in enhancing diversity and suppressing polarization. Further ablation experiments and visualization analysis validated the crucial roles of knowledge graph modeling, cognitive networks, and observation mechanisms within the overall framework, and demonstrated the model's effectiveness and interpretability in semantic representation and propagation path modeling.




(a) Precision in MovieLens1M (b) Recall in MovieLens1M (c) AD in MovieLens1M (d) ARP in MovieLens1M
(e) Precision in LastFM (f) Recall in LastFM (g) AD in LastFM (h) ARP in LastFM
(i) Precision in Amazon-book (j) Recall in Amazon-book (k) AD in Amazon-book (l) ARP in Amazon-book
(m) Precision in Yelp2018 (n) Recall in Yelp2018 (o) AD in Yelp2018 (p) ARP in Yelp2018

**Fig. 9.** Performance comparison across multiple datasets under different recommendation list lengths.

While our proposed method achieved good results in several aspects, certain limitations remain. For example, the modeling of dynamic knowledge updates and cross-domain generalization capabilities needs further improvement. Future work will further explore more efficient dynamic knowledge graph modeling methods and combine causal inference and reinforcement learning mechanisms to achieve more refined public opinion guidance and recommendation strategy optimization. Overall, this paper provides a unified and scalable research framework for intelligent recommendation and collaborative public opinion modeling in a multimedia environment. Future research may focus on modelling temporal semantic evolution to capture continuously changing user interests, emerging events, and dynamic opinion trends within cross-media environments. In addition, dynamic knowledge graph update mechanisms can be investigated to support real-time incorporation of newly generated information and evolving semantic relationships.

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## Declarations

### Data Availability

Not available

### Conflicts of Interest

The authors declared that they have no conflicts of interest regarding this work.

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**Author Contribution**

Wei Lu conceived and designed the study, performed the research, analyzed and interpreted the data, and wrote the manuscript. The author has read and approved the final version of the manuscript and takes full responsibility for the work.

**Ethical Approval**

This article does not contain any studies involving human participants or animals performed by any of the authors.

**Consent to Participate**

Not applicable.

**Consent to Publication**

All authors have provided consent for publication of this manuscript.

**Competing Interests**

The authors declare no competing interests.

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