REVIEW ARTICLE

Recommender System: A Comprehensive Overview of Technical Challenges and Social Implications

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Abstract

The proliferation of Recommender Systems (RecSys), driven by their expanding application domains, explosive data growth, and exponential advancements in computing capabilities, has cultivated a dynamic and evolving research landscape. This paper comprehensively reviews the foundational concepts, methodologies, and challenges associated with RecSys from technological and social scientific lenses. Initially, it categorizes personalized RecSys technical solutions into five paradigms: collaborative filtering, scenario-aware, knowledge & data co-driven approaches, large language models, and hybrid models integrating diverse data sources. Subsequently, the paper analyses the key challenges and future trajectories in five technical domains: general technologies, recommendation accuracy, cold-start problems, explainability, and privacy protection. The review also explores the intersection between RecSys and social sciences, emphasizing how RecSys is shaped by and, in turn, shapes social structures, cultural norms, and societal biases, alongside its influence on decision-making, behaviour, and identity formation. Identified research gaps highlight the need for deeper investigations into cross-cultural variations and long-term effects, as well as for integrating sociological and psychological insights with technical designs. This review systematically encapsulates the current research landscape of RecSys across technological and sociological domains, thereby guiding researchers toward identifying potential advancements and future research directions.

Keywords: recommender system, personalized recommendation, technological roadmap, sociological intersections, psychological implications.

1 Introduction

In the digital era, the rapid advancement of social networking technologies and e-commerce platforms has led to an unprecedented influx of data and heightened information redundancy. This phenomenon has exacerbated the challenge of information overload, drawing considerable attention

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from academic and industrial sectors. Recommender System (RecSys), emerging from the evolution of Artificial Intelligence (AI) technologies in the 1990s, is increasingly recognized as a robust solution to this challenge by addressing the growing demand for personalized services and delivering substantial commercial value [1]. The timeline shown in Figure 1 concisely illustrates the major milestones and phases of change that have shaped the development of RecSys.

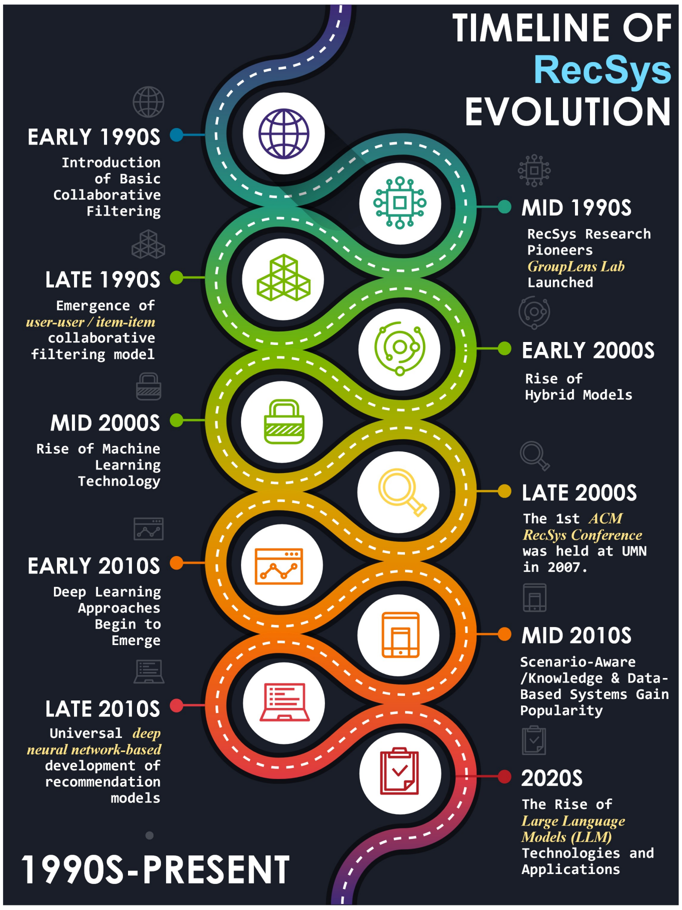

Figure 1. Timeline of RecSys Evolution.

RecSys is deeply integrated with modern intelligent systems through their synergy with sensors, communication, and control technologies. In smart home environments, for example, sensors monitor user habits and relay data via communication networks. This data enables RecSys to provide personalized suggestions while control systems adjust appliance settings autonomously, achieving a sophisticated feedback loop of perception, decision-making, and execution. The seamless integration boosts the precision and promptness of recommendations and cultivates a robust and intelligent management system, leading to a remarkable enhancement in system performance and user satisfaction.

Nevertheless, the evolution of RecSys is accompanied by persistent challenges. The persistence of technical issues such as scalability, cold-start problems, and data sparsity underscores the need for continuous innovation, as selecting optimal methodologies becomes increasingly complex in application-specific contexts. Moreover, the inherently subjective nature of data—shaped by human behavior and societal influences—complicates the notion of objectivity within these systems. As RecSys advances, social implications, including biases, filter bubbles, echo chambers, and data manipulation, have garnered critical attention, particularly from the social sciences. These multifaceted challenges highlight the imperative for ongoing research and interdisciplinary collaboration, setting the stage for a deeper exploration of the technical and ethical dimensions that will shape the future trajectory of RecSys.

Thus, unlike previous surveys on RecSys, past reviews have focused on advanced results and applications in niche areas such as specific tasks or technology lines. This paper is a first-of-its-kind comprehensive review of RecSys from the dual perspectives of technological challenge vein and sociological impact to identify sources for describing RecSys research in AI contexts and human-social explorations. Specifically, this review offers a comprehensive overview of the main paradigms in existing empirical research on RecSys. It also covers the technical challenges associated with RecSys and provides an outlook. Additionally, it delves into the social science issues arising from RecSys and analyzes them in depth. The insights provided in this review are intended to address the dynamics of emerging technologies and societal trends and to guide interested parties to a comprehensive understanding of the theoretical knowledge and optimal deployment scenarios of RecSys, thereby inspiring future research directions.

2 Main Paradigms of Recommender System

Conventional RecSys emphasizes filtering products that might appeal to the users' interests [2]. Expanding on this, more sophisticated RecSys employs personalized methods to assist users in identifying relevant or valuable content from numerous choices or to generate customized recommendations [3]. The expansion of machine learning techniques and the availability of extensive online data resources have facilitated the widespread adoption of personalized RecSys applications for individuals and groups, enhancing users' efficiency in discovering new experiences [4]. As shown in Figure 2, RecSys can now be classified into five main paradigms. This section will provide a detailed discussion of these core paradigms.

2.1 Collaborative Filtering-Based RecSys

Collaborative Filtering-Based (Co-Filter) RecSys is based on the clustering hypothesis and leverages the historical interaction records of a group to build user profiles, which are then used to predict individual user preferences. The operating logic behind Co-Filter is the real-world phenomenon of "word-of-mouth", whereby users with similar preferences in the past are likely to have similar preferences in the future. However, the resulting correlation problem is that the quality of recommendations depends heavily on the availability of sufficient user and item rating information [5]. In particular, it is difficult for Co-Filter to initiate recommendations when brand new subjects (users or projects) with little rating information are added, known as a cold start [6], and we will discuss this issue in detail later. The Co-Filter-RecSys methods are generally divided into three main categories: memory-based, model-based, and contextual-features. The RecSys scoring function's input typically comprises interaction data between users and items. Memory-based methods generate recommendations straightforwardly using user profiles, while model-based approaches utilize mathematical models to produce recommendations, often offering more excellent stability. Additionally, contextual-features recommendations, which incorporate contextual features, exhibit greater complexity and dynamism than user-item interaction data, resulting in improved accuracy.

2.1.1 Memory-Based Collaborative Filtering RecSys

Memory-Based (MemB) Co-Filter-RecSys generates recommendations by measuring the similarity between users or items. Although this method is famous for its simplicity, it faces significant challenges in handling sparse interaction matrices and large-scale computations. Ramadhan et al. [7] combined decision tree methods with user and item models, while Rifai et al. [8] integrated support vector machines. Both studies demonstrated excellent performance on the Twitter dataset. To mitigate computational complexity, embedding techniques commonly convert high-dimensional sparse vectors into low-dimensional dense vectors, thus facilitating similarity calculations. Valcarece et al. [9] introduced the prefs2vec model, inspired by the Continuous Bag-of-Words method in word2vec, for learning user and item embeddings. Chen et al. [10] utilized graph-based methods to derive user and item representations, thereby improving efficiency and speed. Other research, such as that by Barkan et al. [11] and Albora et al. [12], introduced anchor vector-based RecSys and tree-seed similarity allowing negative values, respectively, further enhancing the interpretability of recommendations. Although memory-based Co-Filter-RecSys is not the primary focus of research, it remains significant in scenarios with small datasets or where simplicity and interpretability are prioritized.

2.1.2 Model-Based Collaborative Filtering RecSys

Model-Based (ModB) Co-Filter-RecSys predicts user preferences by analyzing the relationships between users and items. The success of neural networks in learning latent feature spaces has led to the widespread use of Factorization Machines (FM), which excel at integrating various types of features, including categorical and numerical ones. This capability makes FM particularly effective in handling sparse data, especially in user-item interactions, making them a popular choice in large-scale RecSys applications. Zheng et al. [13] introduced the DeepCoNN model, which extracts features from user and item reviews and feeds them into FM to optimize the loss function. Seo et al. [14] utilized a CNN model to separately model users and items, incorporating local and global attention mechanisms to enhance rating predictions. In contrast to sentence-level feature extraction, Chin et al. [15] proposed the Aspect-based Neural Recommender to refine item feature representations. Li et al. [16] employed capsule neural networks to extract opinions from review texts. Wu et al. [17] used CNNs to encode news and user data, applying personalized attention mechanisms to improve performance. On the aspect of interpretability, Liu et al. [18] developed an interpretable RecSys using Graph Neural Networks (GNNs), and Fang et al. [19] employed variational autoencoders to provide accurate recommendations for sensitive information. Additionally, due to the strong capability of GNNs in handling complex user-item relationships, they have gained significant traction in RecSys. Wu et al. [20] improved the robustness of GNNs by employing node and edge dropout techniques. Xia et al. [21] proposed Incremental Graph Convolutional Networks to address the issue of catastrophic forgetting in GNNs. Lin et al. [22] enhanced GNN performance through contrastive learning with neighboring nodes. Zhao et al. [23] developed the r-AdjNorm plugin to address popularity

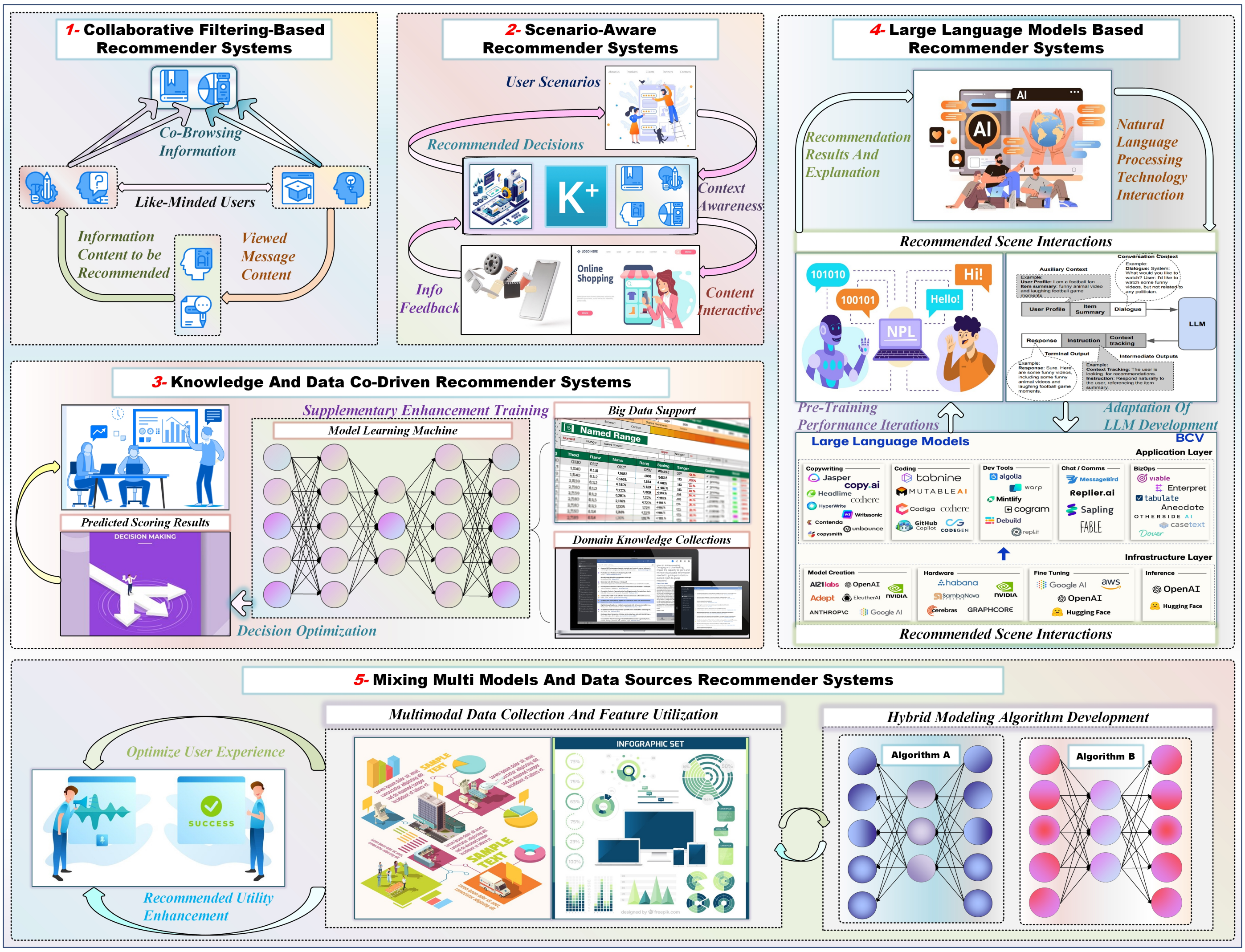

Figure 2. Main paradigms of RecSys.

bias in GNNs. Although ModB-Co-Filter-RecSys has significantly improved recommendation accuracy, further development is necessary to enhance model interpretability and computational efficiency. GNNs have demonstrated unique potential in uncovering deep relationships between users and items and are expected to play a crucial role in future research.

2.1.3 *Contextual-Features Collaborative Filtering RecSys*

The integration of contextual information is crucial for enhancing the decision accuracy of Co-Filter-RecSys. Contextual Features Learning (CFL) Co-Filter approaches require detailed descriptions of users and items as input, with data sources ranging from smart devices that provide location and peer information to direct acquisition through user interests [24]. CFLs are generally more complex and dynamic than user-item interaction data[25]. These advancements enable systems to proactively gather data by analyzing user activities, reducing reliance on self-reported information. However, effectively integrating such information into RecSys remains a substantial challenge. One effective strategy for simplification is dimensionality reduction through latent context embeddings. Mei et al. [26] captured the relationships between context and users or items using an interaction-centered module. Unger et al. [27, 28] employed autoencoders to learn context representations and further group latent context vectors through hierarchical models. To address the limitations of symmetric context-awareness, Ouyang [29] proposed an asymmetric context-aware regulation technique enhanced by GNNs, successfully applied to improve recommendation performance. The selection of a technical pathway is determined by when and where the contextual data is utilized [30]. Pre-filtering eliminates irrelevant information before contextual data is fed into the RecSys, post-filtering applies contextual data after standard recommendation processing, and contextual modeling directly incorporates contextual information into the recommendation model. In Deep Learning (DL), the effective use of contextual information still needs to be improved, which has led to a reduction in computational load. Ebesu et al. [31] developed a CNN-based model to learn context representations. In contrast, Jawarneh et al. [32] implemented a t-statistic-based item splitting algorithm to select context combinations, integrating them into a neural collaborative filtering model through pre-filtering. Wu et al. [33] developed a GCN that extracts information from user-item graphs and their contextual data using an encoder, graph convolution layers, and a decoder. CFL Co-Filter requires datasets to provide rich contextual information to explore latent feature representations and optimize recommendation outcomes deeply. Due to the complexity of integrating contextual information with DL, this area is expected to be a primary focus for future research in CFL Co-Filter-RecSys.

2.2 Scenario-Aware RecSys

Scenario-Aware (Sce-Awa) RecSys enhances personalized recommendations by treating the recommendation task as a user-specific classification problem, learning content-based item feature classifiers. These systems draw on user preference models and interaction history to extract item features, with text data being a primary source. One notable advantage of this approach is its ability to recommend based on item content without needing user ratings. Auxiliary information, such as item metadata or user-generated content, traditionally includes item descriptions or full-text indexing, while extended metadata that introduces external knowledge has also proven crucial.

With the rise of computer vision and multi-modal media features in Sce-Awa-RecSys, DL techniques, particularly in Natural Language Processing (NLP), have seen increased adoption [34]. Van et al. [35] demonstrated that combining word embeddings with personalized preferences leads to superior user profiling compared to traditional Co-Filter. Yang et al. [36] improved recommendation accuracy by employing autoencoders to extract additional features and auxiliary information from open knowledge graphs. Deldjoo et al. [37] utilized pre-trained neural networks to identify stylistic attributes from text, thereby enhancing recommendation outcomes. Cami et al. [38] implemented a posterior inference-based model for user profiling, employing latent clustering to refine recommendation quality. Wang et al. [39] developed a GRU-based content encoder and the CAMO model for text feature extraction, achieving cutting-edge performance through adversarial training. Jesus et al. [40] created a method for identifying personal preferences by analyzing product reviews' essential features, integrating them into a personalized RecSys that accounts for reviewers and end users. Polignano et al. [41] introduced emotion-sensitive computing to build user profiles based on their preferences.

In Sce-Awa-RecSys, Heterogeneous Information Network (HIN) methods have been widespread, enabling the integration of diverse auxiliary information types. These networks provide richer semantic information for item ontologies and link relationships, thus improving recommendation accuracy. Amato et al. [42] generated a user-content social graph from multimedia content, using semantic relevance and low-level feature matching for recommendations. Zhang et al. [43] developed the Spatio-temporal Directed Convolutional Network (STDCN) model to enhance the consistency of location-based recommendations. Ma et al. [44] constructed a heterogeneous bibliographic network using citation information, leveraging meta-paths in the HIN for recommendations. Pham et al. [45] proposed a fuzzy-driven HIN embedding model, combining fuzzy logic with deep network architectures to extract features from unstructured attributes or content.

Sce-Awa-RecSys has matured into a sophisticated system integrating DL, sentiment analysis, HIN, and other technologies and data sources. These developments have significantly enhanced recommendation accuracy and personalization and optimized the overall user experience.

2.3 Knowledge and Data Co-Driven RecSys

The Knowledge and Data Co-Driven (K&D-CoDriv) RecSys does not rely on the interaction history between users and items. This characteristic makes it particularly suitable for complex scenarios where users face cost constraints. For example, in supply chain management, market trends and inventory data are used to optimize purchasing decisions; on education platforms, courses are recommended based on knowledge structure and learning objectives; and in healthcare scenarios, diagnosis and treatment recommendations are provided by combining health data with resource status. These scenarios demonstrate the flexibility and intelligence of K&D-CoDriv RecSys without relying on historical data. The key to this technology lies in the integrated use of domain knowledge encompassing users, items, and their interactions, which supplements and optimizes the input of the recommendation scoring function [46]. These available prior sets include integrated external knowledge [47] and knowledge mined and extracted from datasets [48, 49].

In multi-turn dialogue systems, integrating contextual knowledge about items can significantly improve the effectiveness of natural language generation, highlighting the broad applicability of prior knowledge fusion across multiple domains [50]. This applicability has led to significant academic attention towards K&D-CoDriv-RecSys. For example, in the field of e-commerce, Xia et al. [49] introduced a Knowledge-Enhanced Hierarchical Graph Transformation Network to explore the multiple interaction patterns between users and items by capturing the semantics of specific behavior types and explicitly differentiating the importance of different interactions. Vijayakumar et al. [51] enhanced the adaptability of personalized travel planning recommendations by using user-selected points of interest as temporal features. Huang et al. [52] proposed a Knowledge-Aware Coupled GNN, which improved the encoding of high-order human-item relationships and used mutual information metrics to perceive the global graph structure . Wang et al. [53], when exploring human-item interactions, introduced auxiliary item knowledge and proposed a Knowledge Graph-Based Intent Network, significantly improving the model's generalization performance and interpretability. In advertising and media, Liu et al. [54] enhanced the reasoning ability of news RecSys by combining knowledge graphs with reinforcement learning. In the biomedical field, Gong et al. [55] integrated electronic medical records (EMRs) with a medical knowledge graph through graph embedding techniques, proposing Safe Medication Recommendations (SMR). In software development, Bilal et al. [56] improved the recommendation of developer tools by using query expansion techniques. In healthcare, Cui et al. [57] combined user interaction records and built a knowledge graph to provide more accurate diagnostic and treatment recommendations for patients.

Overall, these diverse studies reveal the broad potential applications of K&D-CoDriv-RecSys across multiple fields such as e-commerce, advertising, biomedicine, software development, and healthcare. These research advancements demonstrate the effective integration and utilization of domain prior knowledge, significantly enhancing RecSys' intelligence.

2.4 Large Language Models-Based RecSys

Although Deep Neural Networks (DNNs) have significantly advanced the development of RecSys, these methods still exhibit notable limitations. For instance, they struggle to generalize and infer effectively across visible and hidden recommendation scenarios. Meanwhile, the rise of Large Language Models (LLMs) has revolutionized the fields of NLP and AI. These models demonstrate exceptional capabilities in core language understanding and generation tasks, along with solid generalization and reasoning abilities. This trend has prompted researchers to explore the application of LLMs' robust functionalities to optimize and enhance RecSys.

With the continuous advancement of generative pre-trained AI technologies represented by LLMs such as ChatGPT, models like LLaMa, Gemini, Yi-Large, and Qwen have emerged. In LLM-Based RecSys, optimizing user-item interactions and information exchanges requires fine-tuning the pre-trained LLMs. Consequently, research into RecSys supported by conversational generation technologies has rapidly expanded. Gao et al. [58] proposed a cross-domain enhanced RecSys based on ChatGPT. Friedman et al. [59] combined LLMs with conversational RecSys by intricately outlining user profiles and demonstrated the fluency and diversity of their model in dialogue generation using YouTube video RecSys.

At the same time, researchers are exploring other methods of fine-tuning LLMs to improve RecSys performance. Bao et al. [60] introduced a two-stage framework, BIGRec, which integrates LLMs into the recommendation space by generating meaningful tokens for items, significantly enhancing recommendation accuracy and applicability. Chu et al. [61] developed the RECSYSLLM system using unique data processing, training, and inference techniques, demonstrating its effectiveness through experiments. Hou et al. [62] designed LLM prompt techniques, showcasing the powerful capabilities of LLM-based RecSys in zero-shot ranking tasks.

Moreover, LLMs have shown excellent potential in enhancing RecSys interpretability and privacy protection. Wang et al. [63] constructed personalized reasoning graphs using LLMs, further boosting the model's effectiveness and interpretability. Carranza et al. [64] combined differential privacy techniques with LLMs, improving overall model performance while safeguarding query-level privacy.

Given LLMs' vast knowledge capacity and human-like interaction capabilities, this technology is anticipated to significantly improve RecSys accuracy and interpretability while addressing cold start issues to some extent. However, current applications of LLM technology are often expensive and resource-intensive, highlighting the urgent need for more lightweight LLM solutions to lower usage barriers and enhance practical feasibility.

2.5 Mixing Multi Models and Data Sources RecSys

The technological evolution of RecSys has led to an exponential increase in implementation complexity for real-world applications. To ensure that RecSys can deliver more accurate recommendations in real-time environments, they often need to integrate various models with multiple data sources, forming a hybrid filtering technique known as Mixing Multi Models and Data Sources (MixM-M&D) RecSys. The deep integration of learning techniques has made it possible to more effectively fuse multi-source information within MixM-M&D-RecSys, such as by combining contextual information with situational content [65]. Moreover, various technical integration strategies are available, such as applying each technique separately and then aggregating the results, or blending model-based approaches with memory-based filtering techniques [66]. Overall, MixM-M&D RecSys can be broadly categorized into Hybrid Model Integration, Multi-Source Data Fusion, Ensemble Learning Techniques, and Cross-Domain Recommendation. The related features are summarized in Table1.

The design of MixM-M&D-RecSys aims to enhance system optimization and overcome inherent technical limitations by integrating multiple recommendation methods and data characteristics. The primary goal is to produce higher quality and more valuable recommendations than what could be achieved by a single algorithm alone. Through this integration, the weaknesses of different algorithms can complement each other, thereby improving the overall quality of recommendations.

The system architecture of the recommendation scoring is typically composed of two or more intermediate functions combined. This combination can be realized in various ways depending on the system's specific needs. For example, Polignano et al. [67] combined user-item interactions with contextual features for recommendations, while Luo et al. [68] mixed graph embedding techniques with contextual information. Contextual information includes dimensions such as historical behavior, social connections, and personal characteristics, underscoring the importance of integrating multiple data sources to enhance the effectiveness of the Recommender System. The advantage of hybrid RecSys lies in its ability to address challenges other algorithms face, such as new user problems and system scalability [69]. However, the complexity and the high implementation costs pose significant challenges that must be considered.

3 Technical Issues for Recommender System

The ongoing advancement of RecSys is driven by the iterative progression between two foundational components: first, the evaluation metrics of RecSys, which are essential benchmarks for assessing the efficacy of research methodologies and technological implementations; second, the intrinsic limitations of the technology, which serve as the impetus for its continuous evolution. Despite significant progress, current RecSys still encounters several unresolved challenges. This section delves into the prevalent technical issues in RecSys research, a summary of which is shown in Figure 3, while also projecting future research directions.

3.1 Generic Technical Aspects of RecSys

RecSys faces substantial challenges in addressing robustness, data bias, and fairness. Robustness refers to the system's resilience against adversarial attacks and its capacity to mitigate such biases' influence effectively. These attacks may manifest through data manipulation, model parameters, or system outputs. Data bias can lead to inaccuracies in user preference data, compromising the recommendations' quality. Such biases may emerge as popularity, selection, exposure, or placement imbalances. The issue of fairness concerns the equitable treatment of both users and items within the system.

Adversarial attacks have become a critical method for assessing the robustness of RecSys. In RecSys tasks, items and users are typically represented as embedding vectors, which provides multiple avenues for attackers to intervene. These interventions may involve manipulating user and item profiles or

Table 1. Main Categories of Mixing Multi Models and Data Sources RecSys.

Method Category	Core Techniques	Application Scenarios	Strengths and Limitations
Hybrid Model Integration	Combines Co-Filter, Sce-Awa, and K&D-CoDriv. Often involves matrix factorization, deep learning models, and rule-based logic.	E-commerce and media platforms where both user interaction data and content metadata are available.	**Strengths**: Combines benefits of multiple models. **Limitations**: High computational cost and tuning complexity.
Multi-Source Data Fusion	Uses techniques like feature concatenation, embedding alignment, and graph-based representations.	Multi-modal data environments (e.g., social media, IoT) with heterogeneous data sources.	**Strengths**: Effective in sparse data settings. **Limitations**: Complexity and noise amplification.
Ensemble Learning Techniques	Bagging, boosting, stacking, or weighted averaging combined with neural networks.	High-stakes fields like finance and healthcare.	**Strengths**: Reduces overfitting and improves generalization. **Limitations**: Reduced interpretability with complexity.
Cross-Domain Recommendation	Transfer learning, domain adaptation, and shared latent space modeling to transfer knowledge across domains.	Platforms with low data volumes, such as new markets or niche products.	**Strengths**: Improves performance in data-sparse domains. **Limitations**: Transferability between domains may be unreliable.

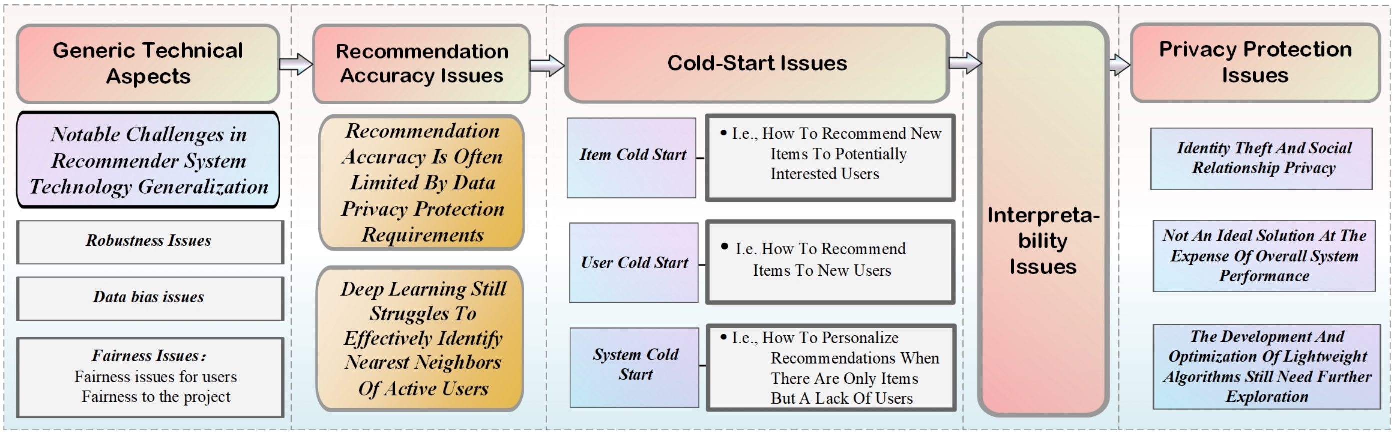

Figure 3. Main technical issues of RecSys.

altering their embedding vectors [70] as leveraging auxiliary information to launch attacks [71]. Two predominant strategies have emerged to counter these vulnerabilities: adversarial training [72] and model distillation [73, 74]. Adversarial training enhances system robustness by introducing controlled perturbations during training, thereby fortifying the model against potential disruptions. On the other hand, model distillation improves robustness through knowledge transfer, effectively addressing vulnerabilities inherent in the system.

RecSys user behavior data is predominantly gathered through observational methods rather than experimental ones, rendering it inherently susceptible to various sources of bias. If these biases are not adequately addressed during the system's design, it can significantly degrade model performance, impair user experience, and erode trust in the system. Therefore, mitigating these biases is of paramount importance. The types of biases commonly encountered in RecSys tasks include popularity bias [75, 76], selection bias [77, 78], and exposure bias [79, 80]. Popularity bias refers to the over-recommendation of popular items, selection bias relates to the influence of user choices on recommendation outcomes, and exposure bias concerns the frequency with which items are presented in recommendations. To address these biases, researchers have developed various debiasing techniques [81], integrating methods such as score calibration loss [82] and propensity score adjustments [79] to enhance model accuracy. These approaches are designed to ensure data fairness, reduce discriminatory outcomes, and strengthen user trust in the RecSys.

Fairness in RecSys encompasses two critical dimensions: user-level fairness, which ensures that recommendations are not biased by users' sensitive attributes, and item-level fairness, which guarantees that each item is given an equitable chance of being recommended. User-level fairness problems can be divided into two categories based on the individual, which focuses on the fair treatment of individual users, and the group, which focuses on the bias of sensitive attributes of the group. Researchers have explored various strategies, including meta-learning MeLU[83], improving adversarial approach [84], differential privacy techniques [85] for individual fairness, and multi-armed bandit algorithms [86] for group fairness. These approaches underscore the importance of tackling fairness issues within advanced machine learning models and highlight the potential advantages of preserving user privacy while enhancing service quality. In terms of item-level fairness, methods such as causal inference [87], idiosyncratic effects of adversarial training [88], meta-learning KoMen [76], and reinforcement learning [89] have been proposed. Each of these methods offers distinct benefits and limitations, suggesting that future research should focus on the deep technical development and extension of these approaches, tailored to the specific requirements of RecSys.

3.2 Recommendation Accuracy Issues in RecSys

As a pivotal branch of data mining, RecSys is significantly shaped by advancements in DL technologies. Their central aim is to perform dimensionality reduction on extensive datasets, thereby facilitating the efficient extraction of latent features from the data [90] to achieve enhanced precision in recommendations. Despite considerable progress, several limitations persist. Primarily, two issues stand out: First, in product recommendations, DL-based models often encounter constraints in recommendation accuracy when dealing with private datasets due to stringent data privacy protection requirements—more extraordinary privacy measures generally result in reduced recommendation accuracy. Second, while DL technologies have exhibited exceptional capabilities in feature extraction, they still face challenges in effectively identifying recent neighbors of active users within memory-based Co-Filter algorithms, thus impeding further advancements in recommendation accuracy.

To address the limitations, current solutions frequently involve integrating reinforcement learning techniques to create hybrid approaches [91]. By leveraging the strengths of both machine learning methodologies, an effective deep reinforcement learning (DRL) framework [92, 93] has been developed. Through its robust self-exploration strategies, this framework has been shown to enhance user interest matching rates. DRL is particularly advantageous in extracting latent future information from user interactions in specific contexts, which can be utilized as auxiliary features in recommendation algorithms, thereby alleviating accuracy issues stemming from insufficient user behavior data. This paper categorizes current DRL methods for improving recommendation performance based on elements such as environment, state representation, and reward function, including value-based (CDQN[94], PDQ[95], GoalRec[96]), hybrid (DeepChain[97], RelInCo[98]), and policy-based (IRecGAN [99], NRSS [100]) approaches in three categories, which are shown in Figure 4. Nevertheless, several technical challenges persist in the experimental design of DRL, primarily including developing more effective reward functions to prevent agents from converging to local optima. Additionally, accurately forecasting future knowledge in human-computer interactions remains a critical issue requiring further investigation.

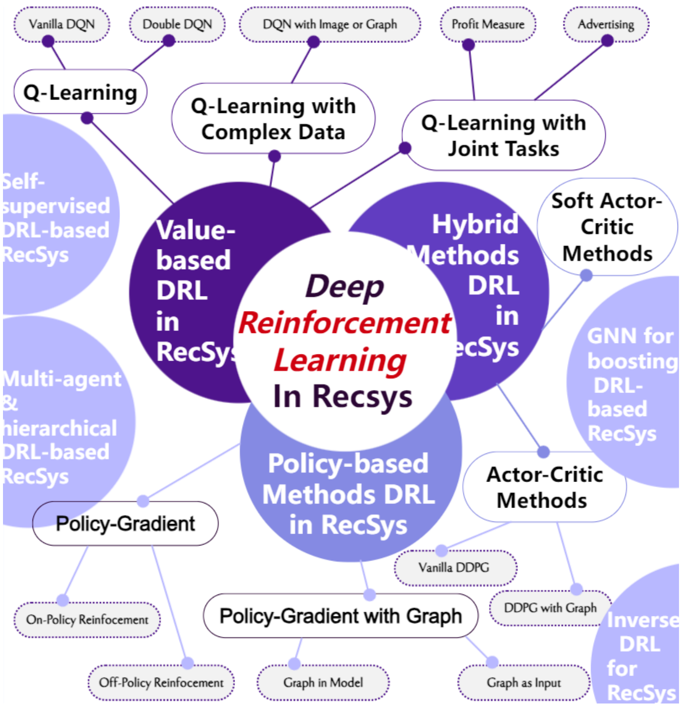

Figure 4. Classification of RecSys based on Deep Reinforcement Learning.

3.3 Cold-Start Issues in RecSys

RecSys algorithms typically depend on extensive historical data to analyze user and item characteristics, predicting potential user preferences. However, for new users, the lack of historical data impedes the system's ability to accurately infer preferences, resulting in recommendation failures—a challenge commonly called the cold start problem. This issue is generally categorized into three types: item cold start (challenges in recommending new items to potentially interested users), user cold start (challenges in recommending items to new users), and system cold start (challenges in achieving personalized recommendations when only items are available but user data is lacking).

The academic community has long focused on this issue to address the cold start problem caused by missing user or item data and proposed several viable solutions. Zhang et al. [101] introduced a kernel-based attribute-aware matrix factorization model for predicting personalized ratings, effectively mitigating the cold start problem resulting from data sparsity. Xu et al. [102] proposed a singular value decomposition algorithm based on trust and behavior. It extracted trust relationships and behavioral features from social networks and incorporated them as supplementary information into the feature matrix to more accurately identify user preferences.

Although the above methods relieve the cold start problem, they do not fundamentally resolve it. Data sparsity continues to exacerbate the complexities of feature extraction and similarity computation. Furthermore, these enhancements are often evaluated on specific datasets, which limits their generalizability. To address the problem at the core, future research should focus on deriving additional relevant information from diverse data sources related to new users or items, thereby compensating for the absence of historical data, employing knowledge graphs for unified semantic representation of multi-source heterogeneous data, constructing case-based reasoning systems, and integrating advanced model frameworks from multimodal and transfer learning approaches. Otherwise, Utilizing multidimensional evaluation metrics to assess proposed solutions' effectiveness rigorously can significantly mitigate data sparsity issues, thereby providing a more robust solution to the cold start problem.

3.4 Interpretability Issues of RecSys

In the ecosystem of RecSys, platform users often passively receive recommendations with a limited understanding of the underlying mechanisms and rationale behind them. To address this limitation inherent in traditional approaches [103, 104], researchers have increasingly focused on enhancing the interpretability of RecSys. A lack of transparency in the decision-making processes of these systems can lead to biases and unfair outcomes, thereby affecting user choices and behaviors. Consequently, understanding and addressing the ethical issues associated with RecSys is crucial for ensuring their responsible and equitable use. In addition, enhancing the interpretability of RecSys helps users better understand the recommendation results and increases their trust in the system, improving the user's stickiness and satisfaction with the platform. With the wide application of personalized recommendations, interpretability is gradually becoming an essential foundation for building responsible and transparent RecSys.

The academic community has introduced various interpretable recommendation methodologies, including recent advancements in sentiment analysis-based algorithms [13]. As research into sentiment analysis has deepened, these methods have been effectively integrated into practical RecSys. For example, Xu et al. [105] proposed the LRPPM-CF framework, enhancing user preference ranking by incorporating tensor matrix decomposition into the LRPPM technology. Additionally, Park et al. [106] developed UniWalk, which combines social network and rating data into a unified graph to learn the latent features of users and items. However, the extensive volume of rating and social network data results in significant computational resource demands, and the method does not support distributed systems. Moreover, Kouki et al. [107] introduced the HyPER system, a probabilistic programmable hybrid RecSys. This system utilizes a combination of statistical models to analyze user preferences and generate recommendations. Despite its capabilities, it lacks personalization and does not fully capture individual user preferences.

To overcome the limitations inherent in single explanation methods, combining the interpretative strengths of recommendation models with those of the recommendations themselves is advantageous by employing knowledge graphs as feature extraction techniques for multi-source heterogeneous data. This approach facilitates the development of hybrid interpretable RecSys based on knowledge graphs [108–110]. Furthermore, it is essential to establish robust user feedback mechanisms and to develop comprehensive standards for evaluating interpretability, thereby effectively leveraging multimodal data. Such an evolutionarily enhanced system can aid users in comprehending the value of recommendations from both the mechanism and the results, as well as improve user satisfaction and maximize the overall efficacy of RecSys.

3.5 Privacy Protection Issues for RecSys

RecSys platforms face the potential risk of privacy breaches in enhancing user convenience due to collecting personal and household data. Addressing the challenge of information overload from large-scale data while safeguarding privacy has emerged as critical. To tackle this, Kim et al. [111] proposed a privacy-preserving method utilizing homomorphic encryption combined with matrix factorization. This approach encrypts user rating data and generates encrypted recommendations through matrix factorization techniques. However, this method has only been evaluated in simulated environments, and its effectiveness in practical applications still needs to be validated. To address issues such as the leakage of sensitive user data and the diminished trust in third-party recommendation services during similarity calculations, Badsha et al. [112] introduced a privacy-preserving protocol for user-centric web service recommendations. This protocol enables untrusted third-party systems to deliver recommendations without disclosing personal information, with minimal impact on service accuracy. Nevertheless, this method exhibits significant inefficiencies in identifying similar user groups. Zhang et al. [113] developed the K-degree Anonymous Friend Recommendation model to combat identity theft and social relationship privacy concerns in conventional RecSys. This model conceptualizes social networks as hypergraphs and employs edge partitioning algorithms to obscure user identities and social connections, thus protecting privacy in friend recommendations within social networks. Despite its advancements, the additional computational overhead associated with hypergraphs indicates a need for further optimization to improve overall system performance.

While the privacy mentioned above protection strategies have positively impacted the prevention of personal information leakage in RecSys across various domains, achieving privacy protection at the expense of overall system performance is suboptimal. With the pervasive use of smart devices and the advent of the 5G era, data privacy issues for these devices—central to social networking, gaming, shopping, and other applications—have become increasingly pressing. Given the computational performance limitations imposed by intelligent terminal hardware constraints and the reduction in recommendation accuracy necessitated by the protection of sensitive user data, there is a compelling need to develop a lightweight protocol that concurrently ensures data privacy and efficient recommendation outcomes [114]. It is crucial to note that the effectiveness of privacy protection is a fundamental prerequisite for implementing such lightweight protocols. Only when the local computational cost for users surpasses the aggregate computational cost of training the recommendation model and generating recommendations will users with limited storage and computational resources be inclined to delegate these tasks to third-party servers endowed with extensive hardware and software resources.

To further mitigate the computational and communication overheads associated with employing Fully Homomorphic Encryption (FHE) for privacy protection in RecSys, researchers have been focused on developing efficient outsourcing computation strategies [115]. Moreover, enhanced FHE schemes can also be utilized in practical applications to reduce the spatiotemporal complexity of encryption algorithms. For instance, the HElib library developed by Halevi et al. [116] optimizes traditional homomorphic encryption algorithms through ciphertext compression techniques, thereby significantly reducing spatial complexity. Despite these advancements in computational performance, the complexity of homomorphic encryption algorithms remains relatively high for resource-constrained mobile users [117]. Consequently, privacy protection solutions for RecSys that rely on public-key homomorphic encryption still face challenges in meeting the practical needs of mobile users, underscoring the need for further development and optimization of lightweight algorithms. Improvements in local differential privacy techniques can be made in the future, which is expected to enable the system to guarantee data analysis accuracy while protecting individual user data's privacy. In addition, advanced methods in the field of federated learning, such as Federated Averaging, are also expected to significantly reduce the risk of data leakage by adapting the development to train the model on local devices and transmit only the model update parameters. Crucially, in the AI era, the issue of privacy protection in RecSys extends beyond computer science to encompass legal, sociological, and other interdisciplinary fields. Interdisciplinary research will be instrumental in comprehensively understanding privacy issues and formulating more effectively tailored solutions.

4 Social Science Issues for Recommender System

RecSys often extends beyond its technical functionalities, functioning as social systems embedded with social values, power dynamics, and cultural implications. This section reviews studies about the intersection of RecSys and social science research. The social sciences encompass a broad spectrum of academic disciplines dedicated to the study of human society and social relationships, with particular emphasis on understanding the structures, dynamics, and functioning of societies, as well as the interactions among individuals and groups within these contexts. The primary objective of the social sciences is to analyze and interpret social phenomena to gain insights into how societies operate, how cultures are formed and sustained, and how social behaviors are shaped by various influencing factors. Technical solutions cannot be developed in isolation from social considerations, and vice versa. To build effective, fair, and trustworthy RecSys, developers and researchers must integrate technical expertise with insights from ethics, sociology, psychology, and public policy. Therefore, this discussion focuses primarily on the interactions between RecSys and the fields of sociology and psychology.

4.1 Sociological Issues in RecSys

The integration of sociological perspectives into the study of RecSys has gained increasing scholarly attention. Analyzing RecSys from a sociological standpoint involves viewing it not merely as a technological tool but as a system deeply embedded in social structures, power relations, cultural dynamics, and human behavior. The data utilized by RecSys are, in essence, social products, and the algorithms trained on this data are susceptible to societal biases related to factors such as gender, race, and class disparities, thus embedding these biases within the RecSys itself. Within the field of sociology, scholars typically emphasize the bidirectional relationship between RecSys and society: societal norms, behaviors, and values influence the design and functioning of these systems, while the systems, in turn, shape societal structures, preferences, and cultural dynamics. Many researchers have underscored this bidirectional relationship between RecSys and society. Social forces and technological design co-produce the outcomes of these systems, including their impact on cultural consumption and social stratification [118]. Studies exploring how societal forces shape RecSys have predominantly focused on several key themes, including the incorporation of cultural norms and values into system design, bias and inequality in data, and ethical considerations. RecSys, in turn, also exerts influence on society, with implications for cultural homogenization, diversity, echo chambers, filter bubbles, and identity formation [119–122]. For instance, RecSys may influence cultural consumption and identity formation by creating "algorithmic imaginaries" — perceptions of what algorithms do and how they influence our choices [123]. Moreover, RecSys can contribute to the formation of echo chambers and filter bubbles, potentially leading to polarized news consumption, political polarization, and societal fragmentation [124].

In recent years, critical approaches and ethical concerns have also emerged as significant areas of discussion. The role of RecSys in digital surveillance and control has sparked broader debates within the social sciences about power dynamics. Zuboff's study was pivotal in exploring the profound changes brought about by the rise of surveillance-based business models. She meticulously examined the history, technology, and mechanisms of surveillance capitalism, highlighting its societal implications. Zuboff argued that tech companies not only monitor but also shape behavior to serve their economic interests, creating asymmetries of power and knowledge that undermine democracy and freedom [125].

Additionally, some studies have addressed ethical challenges related to fairness, transparency, and accountability in RecSys. In contemporary media environments, "algorithmic curation"—a process that is neither neutral nor purely technical, but one that reflects the cultural and social values embedded in algorithms—plays a significant role in democratic participation, knowledge distribution, and the broader public sphere. Algorithmic curation determines what information is visible to users and significantly shapes their online experiences. The power held by these algorithms can profoundly influence public discourse and prioritize content based on engagement metrics rather than informational value [126]. Meanwhile, societal biases encoded by the RecSys can reinforce discrimination and inequality in digital spaces [127].

In order to mitigate the societal biases brought by the RecSys, previous research mainly organized bias interventions at three main stages: the pre-processing phase, model learning phase, and post-processing phase [128]. At the data collection level, biases can be addressed through sampling or missing data from underrepresented groups; at the model training phase, interventions like adversarial learning, rebalancing, and regularization can ensure the system does not reinforce existing biases or concentrate recommendations toward popular item; in the post-processing phase, the output of the recommender system can be adjusted to meet fairness goals, such as ensuring equal representation across different groups [129].

Despite the growing body of research, the sociological implications of RecSys remain underexplored, leaving significant gaps and opportunities for future study for both RecSys and sociology. These gaps stem from the complexities of integrating social theory with algorithmic design and the rapidly evolving nature of both domains. Firstly, although research has begun to address algorithmic bias, there is a need for a deeper exploration of how systemic societal biases—such as sexism and classism—are embedded in RecSys. The technical challenge of bias mitigation is inherently tied to the social challenge of fairness. RecSys often reflects biases present in the training data, including racial, gender, and popularity biases. To avoid marginalizing certain groups, technical solutions must be designed with ethical considerations in mind. Secondly, sociological frameworks could be more effectively applied to better understand the social origins of bias in data, how these biases manifest in recommendations, and how to design systems that mitigate rather than reinforce social inequalities. This approach could provide valuable insights into creating RecSys that promotes fairness and equity. Thirdly, the long-term societal impacts of RecSys, such as their influence on cultural consumption, social behavior, and public discourse, remain insufficiently understood. RecSys is often designed to optimize user engagement by presenting content similar to what users have previously liked, which can lead to "filter bubbles" where users are exposed to only a narrow range of viewpoints or content [121]. This phenomenon can contribute to polarization, limit exposure to diverse ideas, and create echo chambers, particularly in political or social contexts. While short-term effects like filter bubbles and echo chambers have been explored in previous research [124], the broader and more profound social changes that may arise from sustained interaction with these systems are less well understood.

Moreover, although ethical considerations, such as privacy data manipulation, are increasingly discussed in AI and technology studies, there is still a gap in understanding how these concerns manifest in users' everyday experiences and societal outcomes. Additionally, the development of governance models informed by social justice principles for the responsible deployment of RecSys is also underdeveloped. Finally, there is a lack of integrated methodological approaches that bridge sociological insights with the technical rigor of computer science. The divide between qualitative social science research and quantitative algorithmic studies limits the depth and scope of analyses in this field. Addressing this divide would enable more comprehensive investigations and foster a deeper understanding of the interplay between RecSys and societal dynamics.

4.2 Psychological Issues in RecSys

RecSys is increasingly discussed within the field of psychology. Key psychological theories and concepts often discussed alongside RecSys include decision-making and cognitive biases, behavior change and nudging, as well as motivation and engagement [130]. Integrating psychological insights into the design and analysis of RecSys offers mutual benefits: psychology gains new avenues for understanding human behavior in digital environments, while RecSys can be more effectively tailored to address human cognitive and emotional needs.

RecSys significantly shapes the choices presented to users, thereby influencing decision-making processes. RecSys can reinforce and exploit several cognitive biases, such as confirmation bias, availability heuristics, and status quo bias [131, 132]. These biases represent systematic patterns of deviation from rationality in judgment, affecting how users interact with and perceive recommendations [133]. RecSys is designed to lead users toward specific behaviors, drawing on psychological principles from behavioral economics. For instance, RecSys can contribute to habit formation or addictive behavior by consistently recommending similar content that aligns with users' habitual patterns. Consequently, these systems can subtly nudge individuals toward better decisions without restricting their freedom of choice [134].

The evolution of RecSys has gradually shifted from a purely algorithmic focus to a greater emphasis on user experience (UX). Scholars have increasingly highlighted the importance of designing RecSys that are not only technically robust but also intuitive, engaging, and aligned with users' cognitive needs and preferences [135]. Psychologists have focused on user-related aspects such as engagement, motivation, and satisfaction. Psychological principles such as trust, user satisfaction, and cognitive load reduction are frequently discussed in relation to cognitive decision-making processes, demonstrating how well-tailored recommendations can guide user choices and enhance satisfaction by delivering relevant options in a user-friendly manner [136]. User experience is multifaceted and depends on more than just accuracy. Factors such as trust, transparency, and the diversity of options significantly influence how users interact with and ultimately make decisions based on the recommendations they receive [137].

Personalization in recommender systems tailored to individual needs and behaviors based on psychological mechanisms was demonstrated to be crucial. Personalized systems enhance the relevance of recommendations, leading to increased satisfaction, engagement, and trust in the system. By understanding and adapting to individual psychological insights—such as emotion, personality, and decision-making styles, recommender systems can reduce decision fatigue, making interactions more seamless and enjoyable [138]. Personalized recommendations can create a sense of relevance and connection, which in turn boosts engagement rates, repeat visits, and long-term user retention. This is especially critical in e-commerce, streaming services, and social platforms [139]. Different users have varying preferences, decision-making styles, and cultural backgrounds. Personalized recommendations that account for these differences can reduce the risk of alienating certain demographic groups and ensure that the system caters to a broader audience. Tailoring recommendations based on factors like personality, cognitive styles, or cultural context is important to make the experience more inclusive and equitable [140].

Moreover, psychological research has also explored how RecSys impacts identity expression, group identity, social norms, and psychological well-being. RecSys influences how users express and construct their identities, especially on social media and content platforms. For example, in social networks, RecSys can affect users' identity expression, sometimes creating tension between personalization and privacy. Algorithmic recommendations can influence how users present themselves online, occasionally limiting authentic identity expression [141]. Recommendations and feedback mechanisms may also shape user behavior and identity within online communities, revealing that RecSys can influence how users perceive and express their identities within social contexts by curating content based on peer behavior and group norms [144].

Additionally, RecSys can reinforce group identities and social norms by recommending content that aligns with users' social groups [142]. It has been proven by many studies that RecSys can impact psychological well-being, either positively (by aligning content with users' preferences) or negatively (by fostering echo chambers and social comparison) [143]. RecSys may amplify homophily—the tendency to connect with like-minded individuals—which can impact users' mental health by reducing exposure to diverse perspectives and promoting social comparison.

Future research may address several key gaps. There is a need for a deeper exploration of cross-cultural differences in how RecSys is perceived and its varying psychological impacts across diverse populations. Additionally, long-term studies are necessary to understand the enduring effects of algorithmic recommendations on behavior, well-being, and decision-making. Moreover, an interdisciplinary approach integrating psychological insights with computational models will be crucial in designing more user-centric and ethically responsible RecSys. Emerging trends, such as leveraging AI to enhance personalization while mitigating biases and preserving user trust, also present promising directions for future investigation. In this regard, it is essential to explore the integration of humanities and social science theories with recommendation algorithms to promote interdisciplinary innovation.

5 Conclusion

Integrating commercial and technological ecosystems has propelled the Recommender System beyond mere information filtering, transforming them into comprehensive, personalized content-generation tools. On the technical front, collaborative filtering has become the dominant approach due to its robustness, while methods incorporating scenario-aware and knowledge & data co-driven, combined with advanced machine learning, have significantly enhanced system intelligence. Recent research endeavours have actively sought to harness the formidable capabilities of LLMs and the synergistic potential of hybrid methodologies to fortify RecSys. Additionally, scholarly discourse has increasingly focused on addressing dynamic technical challenges, such as generalization, recommendation accuracy, cold start issues, interpretability, and privacy protection. These challenges serve as the driving forces behind the continuous evolution of the field. Moreover, this review critically examines RecSys as social systems, emphasizing its interactions with the domains of sociology and psychology. It highlights the social issues related to RecSys, including the reshaping of social structures and cultural norms, the emergence of echo chambers and filter bubbles, cognitive behaviour disparities, and ethical responsibilities. These multifaceted challenges highlight the necessity for ongoing research and interdisciplinary collaboration, which are crucial for laying the groundwork for ethically sound technological advancements. Such advancements are essential for guiding the future trajectory of RecSys in a manner that aligns with societal values and promotes equitable outcomes.

Overall, as we delve into the field of RecSys, it is clear that personalization is at the intersection of technology and human experience. Based on this, the development of RecSys follows the dual goals of personalization and efficiency optimization, gradually shifting from models of explicit feedback to more sophisticated methods of implicit feedback, context-awareness and multimodal data fusion. As a result, based on the previous comprehensive research summary of RecSys' technological challenges and social impacts, some reflections on its future development trends are condensed. First, from the perspective of the overall technological paradigm, RecSys needs to utilize multimodal technologies to model users, items, and contexts and optimize the positive perceptions of human beings who understand and interact with the natural world in a multidimensional way through multimodal information. Therefore, pre-trained extensive data modelling based on self-supervised learning methods is a feasible direction for RecSys to explore. Its implementation details can be divided into twofold phases: one, the knowledge in the pre-training model can be utilized to improve the system's efficiency, and two, novel pre-training methods for recommendation tasks also need to be explored by improving the structure and objectives of the model. Finally, from the perspective of a cutting-edge application paradigm, RecSys will always focus on user-centred intelligent application development as well as the construction of a responsible evaluation system, focusing on cross-domain collaboration, zero-interaction learning, and adaptive response to the challenges of data sparsity and diversity. We expect the advanced RecSys of the future to provide more accurate, fair, accountable, knowledgeable, transparent and valuable services to improve the community's long-term experience and social impact.

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The authors declare no conflicts of interest.

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