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A Literature Review on Recent Advances in E-Commerce Recommender Systems

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Abstract

Recommender systems have become a cornerstone of modern e-commerce, enabling platforms to provide personalized shopping experiences and improve customer engagement. In the past five years, research has moved beyond classical collaborative and content-based filtering toward advanced architectures powered by deep learning, graph neural networks, reinforcement learning, and multimodal fusion. Recent scholarship has also emphasized the importance of fairness, explainability, and privacy, signaling a broader shift toward trustworthy artificial intelligence. This literature review synthesizes contributions from 2020 to 2025, organizes them into thematic categories, evaluates their benefits and shortcomings, and identifies future directions.

Keywords: Literature review, recommender systems, e-commerce, deep learning, graph neural networks, reinforcement learning, multimodal recommendation, fairness

1. Introduction

E-commerce has reshaped global retail, and recommender systems (RS) are critical in connecting customers with relevant products. Traditional RS approaches—collaborative filtering (CF) and content-based filtering (CBF)—provided the foundation but were limited by sparsity, cold-start, and lack of diversity. Since 2020, scholars have increasingly turned toward advanced machine learning and AI-driven techniques, producing a substantial body of research that requires consolidation.

This literature review provides an organized synthesis of recent works (2020–2025). The review is structured thematically: (a) traditional and hybrid models, (b) deep learning approaches, (c) graph neural networks, (d) reinforcement learning, (e) multimodal recommendation, and (f) trustworthy recommendation.

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2. Classical and Hybrid Models

Although considered traditional, CF and CBF continue to serve as benchmarks. He et al. (2020) demonstrated that simplified graph-based CF models such as LightGCN outperform many complex algorithms by focusing on pure neighborhood propagation. Similarly, Zhang et al. (2023) highlighted the relevance of content-based approaches in domains with rich item metadata. Hybrid strategies combining CF and CBF remain common in commercial systems, though recent literature suggests their dominance is declining in favor of neural approaches.

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3. Deep Learning-Based Recommender Systems

Deep learning has been one of the most widely explored areas in RS research since 2020.

Neural Collaborative Filtering (NCF): Studies such as Xue et al. (2021) reviewed the evolution of NCF and highlighted its effectiveness in capturing non-linear relationships between users and items.

Sequential Models: Petrov and Macdonald (2022) examined BERT4Rec and related Transformer-based models, noting their strong ability to capture short-term user dynamics.

Wide & Deep Learning: Li (2024) discussed hybrid architectures that combine memorization with generalization, which are particularly useful for balancing frequent and rare patterns in e-commerce datasets.

While deep learning models achieve high accuracy, scholars frequently criticize their black-box nature and heavy computational requirements.

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4. Graph Neural Networks (GNNs)

GNN-based RS have grown in prominence due to their ability to model user–item interactions as graphs. Wu et al. (2020) provided a comprehensive survey of GNNs in RS, emphasizing their utility in handling sparse datasets. He et al. (2020) further validated this with LightGCN, showing that pruning non-essential operations leads to efficiency gains without accuracy loss.

Recent works in industrial settings (e.g., Pinterest, Alibaba) confirm that GNNs can be deployed at scale, though scalability and memory consumption remain major obstacles.

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5. Reinforcement Learning Approaches

RL-based RS have emerged as a way to optimize long-term user satisfaction. Chen et al. (2021) provided a survey of RL for recommendation, covering contextual bandits and deep RL. They noted that RL is well-suited for dynamic environments like e-commerce, where user preferences evolve over time.

However, RL approaches are criticized for being resource-intensive and challenging to evaluate offline. Researchers often rely on simulations, which may not generalize to real-world behavior.

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6. Multimodal Recommender Systems

The fusion of multimodal data—such as images, reviews, and metadata—has become increasingly common in domains like fashion and lifestyle products. Sun et al. (2025) surveyed multimodal RS, identifying methods that integrate visual and textual signals for richer representations.

These systems help address cold-start issues, but they introduce complexity in terms of model design and data preprocessing. Scholars also note the high resource demands of multimodal training pipelines.

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7. Trustworthy and Responsible Recommender Systems

Recent research emphasizes the ethical and social dimensions of RS. Ge et al. (2022) and Fan et al. (2022) reviewed fairness-aware and privacy-preserving models, highlighting the risks of bias amplification and lack of transparency in current systems.

Key directions include:

Fairness-aware algorithms that mitigate popularity bias.

Explainable recommendations to improve user trust.

Federated learning for privacy-preserving personalization.

Although these approaches enhance accountability, researchers acknowledge that they often reduce accuracy or increase system complexity.

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8. Comparative Discussion

The reviewed works collectively suggest a trade-off between accuracy, scalability, and trustworthiness.

Deep learning and GNNs offer strong predictive performance but are resource-heavy.

RL provides long-term optimization but is hard to train.

Multimodal systems enhance personalization but increase system complexity.

Trustworthy approaches improve fairness and transparency but may sacrifice accuracy.

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9. Research Gaps and Future Directions

From the literature reviewed, several open challenges remain:

Scalability of GNNs: Need for lightweight models capable of handling billion-scale datasets.

Multimodal fusion frameworks: Development of unified architectures for combining diverse signals.

Fairness benchmarks: Standardized metrics for evaluating bias in recommender systems.

Explainable AI (XAI): Transparent models that balance interpretability with accuracy.

Green RS: Energy-efficient algorithms to reduce environmental impact.

Cross-domain RS: Bridging multiple platforms to provide holistic recommendations.

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10. Conclusion

This literature review analyzed developments in e-commerce recommender systems between 2020 and 2025. The review highlighted the shift from traditional CF/CBF methods to advanced approaches powered by deep learning, graph models, reinforcement learning, and multimodal integration. At the same time, the research community has increasingly addressed issues of fairness, transparency, and privacy. Future scholarship must focus on scalability, accountability, and sustainability to ensure that recommender systems remain both effective and socially responsible.

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