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(Review Article)

FAIRNESS-AWARE RECOMMENDER SYSTEMS IN PRACTICE: A SCOPING REVIEW OF MODELS, EVALUATION PROTOCOLS, AND OPEN CHALLENGES

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ABSTRACT

The recommender systems have emerged as a vital part of digital information platforms, such as those in e-commerce, education, healthcare, and entertainment. However, growing concerns about algorithmic bias, inequality, and the lack of transparency in recommendation systems have increased the need for fairness-aware recommender systems (FARS). Although there has been considerable research development, current studies are scattered across fairness definitions, modelling methods, evaluation methods, and application areas. This scoping review aims to outline the current literature on fairness-aware recommender systems, summarize existing modelling and evaluation methods, present practical applications, and identify research gaps and future directions. A scoping review was conducted using Google Scholar, ResearchGate, ScienceDirect, and Springer, with searches performed up to April 2026 without publication year or geographical restrictions. A total of 1203 records were identified, 557 were screened, 53 underwent full-text review, and 20 studies were included in the final synthesis. A thematic synthesis was conducted to examine fairness concepts, recommendation models, evaluation methods, application domains, and research challenges. The extracted studies were summarized into four themes: fairness concepts and bias sources, fairness-aware recommendation models, evaluation and fairness measurement, and practical applications. The findings indicate that fairness-aware recommender systems increasingly integrate fairness objectives with recommendation performance, while highlighting persistent gaps in evaluation standardization, real-world deployment, scalability, interpretability, and cross-domain validation. Overall, the review demonstrates that fairness-aware recommender systems are fundamental to the development of responsible and trustworthy AI, while emphasizing the need for standardized evaluation frameworks, explainable models, and stronger governance mechanisms to support their effective deployment.

Keywords: Fairness-Aware Recommender Systems, Algorithmic Bias, Ethical AI, Multi-Objective Optimization, Data-Driven Fairness, Equity.

1 INTRODUCTION

Recommender Systems (RS) are now inseparable components of contemporary digital ecosystems, defining the user experiences in the world of e-commerce, streaming services, social networks, and education. These systems enable users to explore large amounts of content because they make suggestions based on their preferences, which improves engagement, satisfaction, and commercial value in the end (Panyavanich et al., 2024). Nonetheless, with the spread of such systems, there has been an issue with unfairness, bias, and transparency. RS might unwillingly reproduce historical disparities, discriminate against certain groups, and support filter bubbles by recommending articles and content based on the user's previous actions (Roy et al., 2024; Chen & Fang, 2025). Fairness-aware recommender systems seek to solve these issues by incorporating algorithms that minimize prejudice and achieve fairness at the same time. Fairness considerations cut across several plains: individual fairness guarantees that analogous users have analogous suggestions, group fairness means that there are inequalities among demographics, and multi-stakeholder fairness addresses the requirements of users, providers, and the goals of the platform (Oware and Amfo, 2025; MoghdasNian et al., 2025). To take a few examples, in academic papers selection, demographic biases can decrease the appearance of the underrepresented researchers, and in e-commerce, algorithmic preferences can overvalue historically popular products at the disadvantage of narrow but valuable niche ones (Bergin, 2025; Panyavanich et al., 2024).

Biases in RS may be introduced at different points which are data collection, model training, or user interactions. Although implicit types of feedback, including clicking history or browsing history, are informative, they might also capture minor biases, which become learned and amplified by the system (Roy et al., 2024). Equally, explicit feedback such as ratings or reviews cannot be just biased by prior exposure, socio-cultural or institutional prestige as in academic recommendation systems (Bergin, 2025). As a result, to reduce bias, but still minimize the quality of recommendations, fairness-aware methods must consider algorithmic methods and evaluation schemes (Brilliantova, 2025). According to recent studies, fairness is not just a technical issue but a question of trust, transparency, and social contribution. Such frameworks as the SAFE-T model in educational AI demonstrate the need to promote fairness, ethical governance, and transparency by stakeholders, and indicate that RS should be interpretable and auditable to achieve user trust (Umoke et al., 2025). Equally, a finance-based article and an airline tourism article show that equity constraints and explainability metrics can be used to improve operational efficiency and inclusivity at the same time (Oware & Amfo, 2025; MoghadasNian et al., 2025).

Recent studies have examined fairness-aware recommender systems from different perspectives, including algorithm design, fairness metrics, evaluation frameworks, and application-specific implementations (Roy et al., 2024; Panyavanich et al., 2024; Zhao et al., 2025). However, these contributions are distributed across different themes and application contexts. Consequently, there remains a need for a scoping review that maps the breadth of this literature, synthesizes the relationships among these areas, and identifies research gaps to guide future work. The reviewed literature frequently concentrates on specific aspects of fairness-aware recommender systems, such as algorithm development (Panyavanich et al., 2024), fairness evaluation and transparency (Bergin, 2025), or domain-specific applications including finance (Oware & Amfo, 2025), education (Umoke et al., 2025), and tourism (MoghadasNian et al., 2025). Although these studies provide important insights, their specialized focus makes it difficult to obtain a consolidated understanding of how fairness is conceptualized, implemented, and evaluated across different recommendation settings. A few synthesized studies exist in the relationship between these concepts of fairness, models, evaluation frameworks, and real-world applications, consequently leading to gaps in knowledge that limit the ability to practically deploy them.

This review focuses on the practice of fairness-aware recommender systems, including diversity of models, evaluations, and applications, as well as the unresolved issues across multiple application domains and geographical contexts. By incorporating evidence from diverse settings, the review provides a broad understanding of how fairness is conceptualized, implemented, and evaluated in recommender systems.

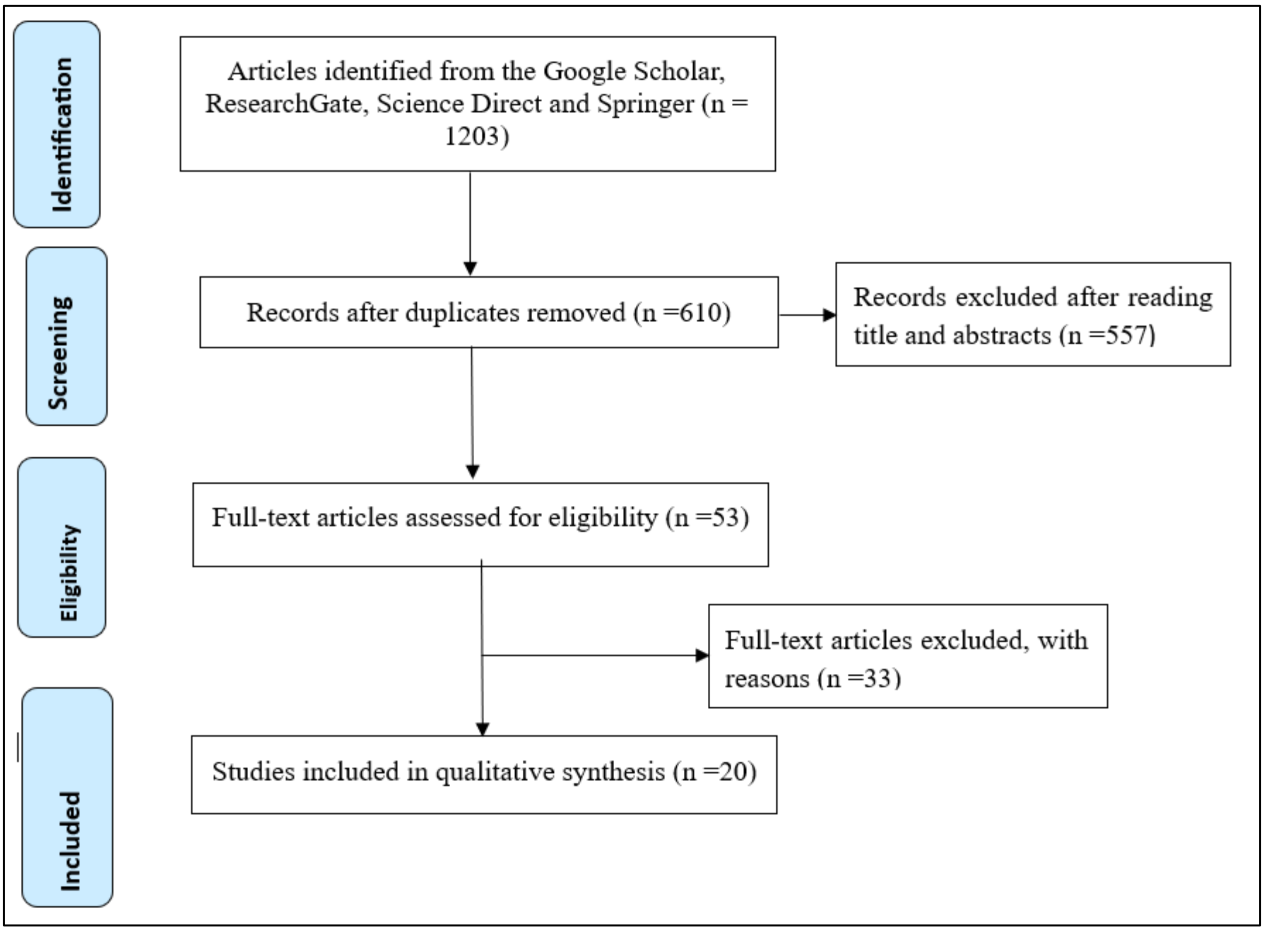
2 METHODOLOGY

In this study, a scoping review method was used to understand the scope of the literature and to find research gaps in fairness-aware recommender systems. The combinations of search terms “fairness-aware recommender systems”, “fair recommendation”, “algorithmic bias”, and “recommender systems fairness” were used to search the literature through Google Scholar, ResearchGate, Science Direct and Springer without publication year limitation up to April 2026. No restrictions on publication year were imposed to provide for both the early and current developments in the field.

Thematic analysis was used to synthesize the studies and analyze the concept of fairness, recommender models, evaluation methods, areas of application, and issues in recommender systems. Thematic analysis was used to include and synthesize full-text studies to analyze the concepts of fairness, recommender models, evaluation methods, areas of application, and issues in recommender systems. Studies that did not address general AI fairness in the absence of a recommender system, duplicate records, and studies not related to recommender systems were excluded. The aim of this review was also to give an overview of the literature and not to systematically review all the available evidence. The review included papers from various areas and geographical locations to enable a wide map of research for Fairness in Recommender Systems. 10 studies were found following the inclusion criteria and included in the review. The included studies have been grouped into four main themes: fairness concepts and sources of bias, fairness-aware recommendation models, evaluation and fairness measurement, and real-world applications in domains. The information extracted was then analyzed and synthesized thematically to detect common patterns and key research areas that emerged from the literature.

2.1 Study Selection

A total of 1203 records were retrieved from Google Scholar and Research gate through Literature Search. After initial screening, 557 records were taken out for title and abstract. 53 studies were then fully text screened for eligibility. After applying the inclusion and exclusion criteria, 20 studies were included in the final review and formed the basis of the thematic synthesis. To ensure that only articles related to recommender systems were considered, those that did not touch on the concepts of fairness were not included; similarly, articles that covered broader AI applications outside of the recommender system context were also excluded.



Sources; Author's Construct 2020

Figure 1: PRISMA Flow Diagram

2.2 Characteristics of Included Studies

The characteristics of the included studies are as follows:

The studies included in this book span a variety of application areas, notions of fairness, recommendation models, and evaluation methods. The literature comprised conceptual studies, surveys, framework proposals, methodological developments and domain-specific applications. Most studies were on mitigating bias, making fair recommendations, studying fair performance trade-offs, or studying practical deployment issues. The studies included did not necessarily happen in one country or region. This diversity is indicative of the global nature of fairness-related challenges in recommender systems and allows for identifying common trends across different domains.

Table 1: Characteristics of Included Studies

Author(s)	Domain	Main Focus	Key Contribution
Roy et al. (2024)	General RS	Fairness, bias, privacy	Comprehensive analysis of fairness and bias in recommender systems
Chen & Fang (2025)	General RS	Fairness concepts	Classification of fairness paradigms and bias sources in recommender systems
Brilliantova (2025)	General RS	Fairness-aware recommendation models	Review of graph-based, deep learning, and hybrid approaches for fairness-aware recommendations
Panyavanich et al. (2024)	E-commerce	Recommender systems	Review of recommendation techniques and challenges
Zhao et al. (2025)	General RS	Fairness and diversity	Survey of fairness-aware recommendation approaches
Bergin (2025)	Academic recommendation	Fairness in scholarly recommendations	Fairness in academic paper selection
Smajić et al. (2025)	General RS	LLM-based recommender systems	Exploration of large language model and multi-agent approaches for improving fairness in recommender systems
Solanke (2025)	General RS	Algorithmic fairness and AI governance	Discussion of fairness, transparency, accountability, and ethical governance in AI-driven recommender systems
Bin et al. (2025)	Recommendation models	Counterfactual fairness	Fairness-aware recommendation through representation learning
Wang et al. (2025)	Code review recommendation	Multi-agent fairness	Fair recommendation of code reviewers
Kowald (2024)	General RS	Transparency and fairness	Review of transparency, privacy, and fairness
Oware & Amfo (2025)	Finance	Fair credit scoring	Framework for fairness and bias mitigation
Umoke et al. (2025)	Education	Fair educational AI	SAFE-T framework
MoghadasNian et al. (2025)	Tourism	Fair generative AI recommendations	Equity and accessibility in tourism recommendations
Amoako et al. (2025)	General RS	Hybrid recommendation models	Examination of hybrid machine learning approaches for improving recommendation performance and fairness

3 RESULTS AND THEMATIC FINDINGS

Based on the literature, the thematic analysis revealed four main themes: fairness concepts and sources of bias; fairness-aware recommendation models; evaluation and measurement of fairness; and applications of fairness-aware recommender systems.

3.1 Fairness Concepts and Sources of Bias

Eight of the fifteen included studies examined fairness concepts and sources of bias, making this one of the most prominent themes identified in the review (Roy et al., 2024; Zhao et al., 2025; Chen & Fang, 2025; Bergin, 2025; Bin et al., 2025, Kowald, 2024; Solanke, 2025; Umoke et al., 2025). These studies conceptualized fairness as extending beyond recommendation accuracy to include equitable treatment of users, items, and multiple stakeholders. Data bias, algorithmic bias, and interaction bias were consistently identified as the principal sources of unfairness affecting recommendation outcomes, while transparency, accountability, and stakeholder trust emerged as essential considerations in fairness-aware system design. The studies included provide complementary perspectives on these issues. For instance, Roy et al. (2024) identified data, algorithmic, and interaction bias as key challenges capable of reinforcing existing inequalities within recommender systems and emphasized integrating fairness alongside privacy and transparency. Zhao et al. (2025) highlighted individual, group, and multi-stakeholder fairness as the dominant fairness paradigms and argued that fairness objectives should be selected according to the recommendation context and stakeholder needs. Similarly, Bergin (2025) demonstrated the importance of transparency and equitable representation in academic recommendation systems, showing that fairness influences not only recommendation quality but also the visibility of researchers and scholarly outputs.

These findings indicate that fairness has evolved from a purely algorithmic concern into a broader socio-technical principle that should be considered throughout the recommendation lifecycle. From a research perspective, this highlights the need for greater consistency in defining and operationalizing fairness across different recommendation contexts. For practice and policy, the findings emphasize incorporating fairness assessment, transparency, and accountability into the governance and deployment of recommender systems to support responsible and trustworthy AI.

3.2 Fairness-Aware Recommendation Models

A significant number of studies also explored modelling approaches for achieving fairness in recommender systems (Panyavanich et al., 2024; Brilliantova, 2025; Wang et al., 2025; Smajić et al., 2025, Bin et al., 2025; Zhao et al., 2025; Kowald, 2024; Amoako et al., 2025). Across these studies, matrix factorization, graph-based models, deep learning techniques, multi-objective optimization frameworks, and hybrid architectures were identified as the dominant approaches for balancing recommendation utility with fairness objectives. More recent studies also reported increasing interest in LLM-based and multi-agent recommendation frameworks capable of addressing multiple fairness objectives simultaneously. The reviewed studies demonstrate the diversity of existing modelling strategies. Panyavanich et al. (2024) discussed traditional recommendation approaches and emerging hybrid models, emphasizing the importance of integrating fairness constraints without substantially compromising recommendation quality. Brilliantova (2025) highlighted the strengths of graph-based and deep learning models in capturing complex user-item relationships while addressing fairness considerations. In addition, Wang et al. (2025) examined multi-agent recommendation frameworks designed to improve fairness through collaborative decision-making, whereas Smajić et al. (2025) reported the growing role of LLM-based approaches in supporting adaptive and context-aware recommendations.

Collectively, these findings suggest that no single modelling approach is universally applicable across all recommendation scenarios. Instead, the selection of fairness-aware models should be guided by application requirements, stakeholder priorities, available data, and fairness objectives. For researchers, this underscores the importance of developing adaptive and explainable recommendation models. For practitioners and policymakers, the findings reinforce the need to evaluate recommendation models not only by predictive performance but also by their ability to produce equitable and transparent outcomes.

3.3 Evaluation and Fairness Measurement

Although a number of studies mention fairness measurements, three of the fifteen included studies focused specifically on evaluating fairness-aware recommender systems (Bin et al., 2025; Bergin, 2025; Zhao et al., 2025). Together, these studies reported that fairness evaluation increasingly combines conventional recommendation performance metrics, such as Precision, Recall, and Normalized Discounted Cumulative Gain (NDCG), with fairness-specific measures including statistical parity, exposure fairness, and disparity indicators. However, the reviewed studies consistently noted considerable variation in evaluation frameworks and benchmarking procedures. Representative studies illustrate this diversity. Bin et al. (2025) incorporated fairness metrics alongside predictive performance measures to assess recommendation quality while minimizing bias. Bergin (2025) demonstrated how fairness evaluation can improve equitable representation in academic recommendation systems by considering transparency and stakeholder fairness in addition to recommendation accuracy. Zhao et al. (2025) further highlighted the absence of standardized evaluation protocols, observing that differences in fairness objectives and application contexts make meaningful comparisons across studies difficult.

The findings indicate that fairness evaluation has become an essential component of recommender system assessment but remains methodologically inconsistent. For research, this highlights the need for standardized evaluation protocols and benchmark datasets to improve comparability and reproducibility. From a practical and policy perspective, adopting consistent evaluation frameworks would support more transparent assessment of fairness interventions and facilitate the responsible deployment of recommender systems across different sectors.

3.4 Fairness-aware Recommender Systems Applications

Most included studies examined the practical application of fairness-aware recommender systems across finance, education, healthcare, e-commerce, and tourism (Oware & Amfo, 2025; Umoke et al., 2025; MoghadasNian et al., 2025; Roy et al., 2024; Zhao et al., 2025, Bergin, 2025; Panyavanich et al., 2024; Wang et al., 2025; Bin et al., 2025). Across these application domains, fairness-aware recommender systems were consistently used to improve equitable access to information, services, and opportunities while reducing bias in recommendation outcomes. Several studies illustrate the breadth of these applications. Oware and Amfo (2025) demonstrated the importance of fairness-aware recommendations in financial decision-making by addressing bias within credit-related systems. Umoke et al. (2025) proposed the SAFE-T framework to support fairness, accountability, and transparency in educational recommendation systems. MoghadasNian et al. (2025) highlighted fairness considerations within tourism recommender systems, emphasizing equitable destination exposure and accessibility for diverse users. Together, these studies show that fairness-aware recommender systems are increasingly being applied in domains where recommendation outcomes directly influence opportunities and resource allocation.

The findings demonstrate that fairness has become an important consideration across multiple sectors rather than being limited to traditional recommendation environments. From a research perspective, this highlights the need to evaluate fairness-aware recommender systems across more diverse real-world settings. For practice and policy, the evidence supports integrating fairness principles into organizational governance and AI deployment strategies to promote equitable, transparent, and socially responsible recommendation services.

Table 2 summarizes the major categories of fairness-aware recommender system models, their practical applications as highlighted in the themes, together with strengths, and limitations identified in literature.

Table 2: Models for Fairness-Aware Recommendations

Model Type	Description	Practical Example	Strengths	Limitations
Matrix Factorization / Collaborative Filtering	This breaks down user-item interactions into latent factors (fairness constraints integrated for equitable representation)	Academic writing suggestion: enhance the visibility of the underrepresented authors. E-commerce: balances between the popular and the niche products (Bergin, 2025; Panyavanich et al., 2024).	Effective when demographic or group information is available, factor contributions can be interpreted.	The interaction is limited, meaning it is less effective without group information.
Graph-Based Models	The user and items are viewed as the nodes in a network; fairness spreads among the relationships.	Social networks: equitable link prediction fairness (Brilliantova, 2025). Code Reviewer recommendation: equitable resource distribution code review (Wang et al., 2025).	Represents complicated relational arrangements which are appropriate where there are multi-stakeholders.	It is too costly to compute on large networks and may need to preprocess graphs.
Deep Learning Approaches	Neural networks and attention models that capture complex nonlinear patterns. It provides fairness through regularization, adversarial learning, or fairness-based loss functions (Kowald, 2024).	ACM Special Interest Group on Computer-Human Interaction (SIGCHI) paper recommendation: it aims at utility of h-index, fairness (Bergin, 2025). Airline tourism: itinerary personalization with generative AI that is equitable (MoghadasNian et al., 2025).	Supports high-dimensional nonlinear relationships and accommodates a variety of fairness constraints.	Computationally intensive and needs to be tuned to balance fairness and accuracy.

Multi-Objective Optimization Models	Optimizes the quality of recommendations, fairness, and diversity simultaneously, and compromises between objectives.	FAIR-MATCH: relevance, fairness, and diversity have equal importance (Zhao et al., 2025). Enterprise AI: the ethical trade-offs are measured (Solanke, 2025).	Explicitly balances multiple objectives and quantifies fairness-utility trade-offs.	Needs close weighting of goals, hence, can decrease the accuracy when fairness weight is excessively high.
Hybrid and LLM-Based Approaches	Combines various strategies (MF, deep learning, graph embeddings) and LLMs to enhance multi-stakeholder fairness on the domains (Amoako et al., 2025).	Airline tourism: equity and accessibility, which is conditional (MoghadasNian et al., 2025). Scholarly code review: multi-agent fairness coordination (Wang et al., 2025). Also applied in areas including business, clinical, and social sciences to guarantee increased equity and personalization (Smajić et al., 2025).	Builds on the advantages of various approaches. It can be scaled to a wide variety of fields. It promotes the fairness of multi stakeholders.	Complicated design and implementation and have to incorporate heterogeneous models and LLMs.

Matrix factorization models have been useful in tackling explicit fairness constraints between users and items but may be limited in capturing complex interactions. Graph-based models represent relational dependencies and are well suited for social and networked systems. Deep learning approaches are highly expressive and capable of modeling complex patterns, although they often require interpretability mechanisms and fairness-aware loss functions. Multi-objective optimization models explicitly balance fairness, utility and diversity and are therefore applicable in multi-stakeholder contexts. Finally, Hybrid and LLM-based approaches can address fairness in multiple domains with changing constraints.

The reviewed studies show a growing trend towards the use of hybrid and learning-based frameworks that can allow for multiple fairness goals, in contrast to traditional ways of recommending. However, no single model consistently achieves optimal performance across all fairness dimensions and application contexts, indicating that fairness-aware recommendation remains highly context-dependent. This mapping of model categories identifies the variety of models that have been developed and the areas where research is needed. These models make a toolkit which can be adapted to fields like finance, education, e-commerce, tourism, and academic suggestions, based on the data structure, fairness goals, and system objectives (Oware & Amfo, 2025).

4 DISCUSSION

The thematic synthesis demonstrates that fairness-aware recommender systems have evolved into a multidisciplinary area of research that extends beyond improving recommendation accuracy to addressing broader concerns of equity, transparency, accountability, and responsible artificial intelligence. Across the included studies, fairness was consistently conceptualized as a multidimensional construct encompassing individual fairness, group fairness, and multi-stakeholder fairness, reflecting a shift from performance-centred recommendation towards socially responsible system design (Roy et al., 2024; Zhao et al., 2025; Chen & Fang, 2025; Solanke, 2025). This evolution suggests that fairness is increasingly recognized as a fundamental design principle rather than an optional enhancement to recommender systems.

The four themes identified in this review further demonstrate that fairness-aware recommendation is shaped by the interaction between fairness concepts, recommendation models, evaluation approaches, and practical implementation. The reviewed studies indicate that achieving fairness depends not only on the choice of recommendation algorithm but also on how fairness is defined, measured, and operationalized within specific application contexts (Panyavanich et al., 2024; Brilliantova, 2025; Bin et al., 2025; Bergin, 2025). Consequently, fairness should be considered throughout the recommendation pipeline, from data collection and model development to evaluation and deployment.

The findings also reveal considerable methodological diversity within the field. The included studies reported the use of matrix factorization, graph-based methods, deep learning, multi-objective optimization, hybrid architectures, and emerging LLM-based and multi-agent approaches to improve fairness in recommendation outcomes (Wang et al., 2025; Smajić et al., 2025; Brilliantova, 2025; Zhao et al., 2025). However, the evidence does not identify a single modelling approach as universally effective across all application domains. Rather, the suitability of a fairness-aware model appears to depend on the recommendation context, stakeholder requirements, data characteristics, and fairness objectives being addressed.

Another important finding concerns the evaluation of fairness-aware recommender systems. Although the reviewed studies increasingly combine conventional recommendation metrics with fairness-specific measures, they also consistently report variation in evaluation protocols and benchmarking procedures (Bin et al., 2025; Bergin, 2025; Zhao et al., 2025; Kowald, 2024). This lack of methodological consistency limits the comparability and reproducibility of findings across studies and highlights the need for more standardized evaluation practices to support the broader adoption of fairness-aware recommender systems.

Finally, the extent of application domains represented in the reviewed studies, which include finance, education, healthcare, e-commerce, tourism, academic recommendation, and software engineering, demonstrates that fairness has become an important consideration wherever algorithmic recommendations influence access to information, services, or opportunities (Oware & Amfo, 2025; Umoke et al., 2025; MoghadasNian et al., 2025; Bergin, 2025; Wang et al., 2025). These findings indicate that future progress in fairness-aware recommender systems will depend not only on advances in recommendation algorithms but also on stronger evaluation frameworks, interdisciplinary collaboration, and governance mechanisms that support the responsible, transparent, and equitable deployment of recommender systems across diverse application domains (Roy et al., 2024; Zhao et al., 2025; Solanke, 2025).

5 OPEN CHALLENGES AND GABS

The mapped evidence reveals several important knowledge gaps that continue to limit the advancement and practical implementation of fairness-aware recommender systems. First, considerable variation exists in how fairness is conceptualized and evaluated across the reviewed studies. Although individual, group, and multi-stakeholder fairness were widely discussed, no standardized conceptual or evaluation framework emerged, making it difficult to compare findings across studies and application domains (Roy et al., 2024; Zhao et al., 2025; Bergin, 2025). This lack of consistency is further reflected in the diverse combinations of fairness and utility metrics adopted by different studies, which limit reproducibility and benchmarking.

The review also indicates that much of the existing evidence is derived from experimental datasets and controlled evaluation environments, with comparatively few studies examining the long-term performance and deployment of fairness-aware recommender systems in real-world settings such as healthcare, education, finance, and e-commerce (Oware & Amfo, 2025; Umoke et al., 2025; MoghadasNian et al., 2025). In addition, although a wide range of recommendation models has been proposed, limited evidence was found regarding their scalability, explainability, and generalizability across diverse datasets and application contexts (Brilliantova, 2025; Wang et al., 2025; Smajić et al., 2025). The mapped studies also provide relatively little evidence on the transferability of fairness-aware approaches across organizational and geographical contexts, suggesting that fairness remains highly dependent on domain-specific requirements and implementation environments (Roy et al., 2024; Zhao et al., 2025). Collectively, these gaps indicate that further methodological and empirical research is needed to strengthen consistency, applicability, and practical adoption of fairness-aware recommender systems.

Future Research Directions

Building on the gaps identified in this review, future research should prioritize the development of standardized fairness frameworks that provide consistent definitions, evaluation metrics, and benchmarking procedures for fairness-aware recommender systems. Such frameworks would improve comparability across studies and facilitate the accumulation of robust evidence for both researchers and practitioners. Future investigations should also extend beyond experimental settings by evaluating fairness-aware recommender systems in real-world environments and through longitudinal studies, particularly in sectors where recommendation outcomes influence access to services, education, healthcare, finance, and other high-impact decisions. Future work should further focus on developing recommendation models that jointly optimize fairness, recommendation quality, scalability, transparency, and explainability while remaining adaptable to different application domains and stakeholder requirements. Integrating explainable artificial intelligence techniques into fairness-aware recommendation models may enhance user trust and support more transparent decision-making processes. Finally, greater emphasis should be placed on cross-domain validation and interdisciplinary collaboration involving researchers, industry practitioners, domain experts, and policymakers. Such collaborative efforts will be essential for developing governance frameworks, establishing best practices, and supporting the responsible, equitable, and sustainable deployment of fairness-aware recommender systems across diverse organizational and geographical contexts.

6 CONCLUSION

This scoping review was to summarize the current landscape of fairness-aware recommender systems by collecting evidence from the reviewed studies on the concepts of fairness, recommender systems models, evaluations, and applications.

The findings demonstrate that fairness has evolved into a fundamental consideration in recommender system design, extending beyond predictive accuracy to encompass transparency, accountability, and equitable outcomes for multiple stakeholders. Despite the progress made in fairness-aware modelling and evaluation, gaps in standardized fairness frameworks, validation on real-world, scalability, explainability and cross-domain applicability were identified. The results show the importance of having more standardized approaches and inter-disciplinary teams for supporting responsible utilization of recommender systems. These challenges will help advance trustworthy, transparent and equitable recommendation technologies that will be able to address the needs of diverse application areas and diverse stakeholders.

STATEMENTS ON COMPLIANCE WITH ETHICAL STANDARDS

Disclosure of conflict of interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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