COSC 520 Presentation: Recommender Algorithms

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This report examines modern recommender systems with a focus on their historical development, core algorithmic structure, and societal implications. We analyze issues related to privacy, fairness, psychological well-being, and ideological escalation. Finally, we discuss potential technical and ethical solutions that align recommender systems with user well-being and platform accountability.

1 Introduction

Recommender systems shape how billions of users discover content, products, and information online. Platforms such as YouTube, TikTok, Netflix, and Amazon rely heavily on large-scale deep learning models to rank and personalize content. This report investigates how these systems evolved, how modern algorithms function, what societal and personal risks they create, and what solutions can be used to mitigate these issues.

2 Algorithmic Background

The evolution of recommender algorithms from simple rule-based systems to deep learning architectures has been driven by data growth, computational advances, and the economic value of personalization. This evolution provides context for examining the privacy, fairness, and ethical challenges of modern recommender systems.

2.1 Early Approaches: Content-Based and Demographic Filtering

Content-based filtering recommends items similar to those a user has previously liked, using item features and user preferences to compute similarity [11]. For example, recommending movies with similar genres or actors. While intuitive and privacy-preserving, these systems suffer from limited diversity and cannot leverage collective user patterns.

Demographic filtering recommends items based on age, gender, or location, assuming users in similar demographic groups share preferences. However, this naive approach often reinforces stereotypes, and its effectiveness is limited in a diverse, modern world. These limitations motivated the development of collaborative filtering.

2.2 Collaborative Filtering: Leveraging Collective Intelligence

Collaborative filtering marked a paradigm shift in recommender systems. Resnick et al. [12] introduced GroupLens, pioneering the idea that users who agreed in the past will likely agree in the future. User-based collaborative filtering identifies users with similar rating patterns and recommends items those users enjoyed. This enables serendipitous discovery and leverages collective intelligence. However, computing similarities between all user pairs becomes computationally prohibitive as the user base grows.

To address this issue of scalability, Linden et al. [8] developed item-to-item collaborative filtering at Amazon. This approach computes item similarities based on user co-interactions. Since items typically grow more slowly than users, and item similarities remain stable over time, they can be pre-computed. Despite these advances, collaborative filtering still faced cold-start problems (inability to recommend for new users or items with no interaction history) and sparse rating

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matrices (users rate only a tiny fraction of available items, leaving insufficient overlap for similarity computation).

2.3 Matrix Factorization: Uncovering Latent Factors

The Netflix Prize competition (held from 2006-2009) prompted the introduction of many novel matrix factorization techniques. Among the most influential contributions, Koren et al. [7]—whose work was central to the winning solution—decomposed the sparse user-item rating matrix into two lower-dimensional matrices representing users and items in a shared latent factor space. Mathematically, the rating matrix $R \in \mathbb{R}^{m\times n}$ (with m users and n items) is approximated as $R \approx U \cdot V^T$, where $U \in \mathbb{R}^{m\times k}$ represents user latent factors, $V \in \mathbb{R}^{n\times k}$ represents item latent factors, and $k \ll \min(m, n)$ is the number of latent dimensions. Each row u_i in U is the latent factor vector for user i, and each row v_j in V is the latent factor vector for item j. The predicted rating for user i and item j is computed as $\hat{r}_{ij} = u_i \cdot v_j^T$, the dot product of their respective latent vectors [7].

This approach handles sparsity, provides dimensionality reduction for computational efficiency, and captures meaningful latent concepts. These latent concepts would otherwise not be discoverable through manual feature engineering, as they emerge automatically from user-item interaction patterns. Techniques like SVD and ALS became the standard methods for learning these factorizations [7]. However, matrix factorization assumes linear relationships and cannot easily incorporate temporal dynamics or rich metadata, motivating later exploration of non-linear approaches.

2.4 Deep Neural Networks: Modern Architectures

Deep learning revolutionized recommender systems by enabling the use of complex, non-linear representations. Covington et al. [3] described YouTube's two-stage architecture: candidate generation (producing user embeddings to retrieve candidates) and ranking (scoring candidates using hundreds of features). Neural networks model non-linear feature interactions, incorporate heterogeneous features (categorical, continuous, sequential), and leverage transfer learning. These capabilities enable models to capture complex user preferences that linear methods miss and combine diverse data types into a single framework, while pre-trained representations improve performance with limited data.

He et al. [6] introduced Neural Collaborative Filtering (NCF), which generalizes matrix factorization by replacing the dot product with a multi-layer network learning arbitrary interaction functions. Despite strong performance, deep recommenders require substantial computational resources, lack interpretability, and amplify privacy concerns by encoding societal biases from training data [18].

2.5 Current Trends and Hybrid Approaches

Contemporary recommender systems employ hybrid approaches combining collaborative filtering, matrix factorization, and deep learning. State-of-the-art techniques include graph neural networks for user-item-context relationships [16], reinforcement learning for long-term engagement [1], and context-aware recommendations. While these advances improve recommendation quality, they simultaneously create three critical challenges: privacy risks from increased data collection and model complexity, fairness concerns as sophisticated algorithms encode and reinforce societal biases, and ethical issues from engagement-driven optimization that may promote radical ideologies and manipulative content.

3 Analysis of Societal Impacts

Recommender systems influence not only what users see online, but also how they behave, what information they receive, and how they perceive the world. This section surveys key societal risks identified across multiple research studies, examining privacy concerns, fairness and exposure inequalities, psychological effects, and risks of ideological escalation. Together, these findings illustrate how engagement-optimized algorithms can create complex challenges beyond their technical objectives.

3.1 Privacy Risks: Profiling, Inference and Transparency

Modern recommender systems rely heavily on behavioural data, such as clicks, searches, and viewing time, to construct detailed user profiles. As noted in Zhang et al. (2014) [17], much of this information is gathered implicitly, without explicit user awareness, which can contribute to perceptions of intrusiveness.

A key concern is the system's ability to infer sensitive attributes. Even when users do not provide demographic or personal details directly, behavioural patterns may allow the system to infer characteristics such as age, gender, or health-related interests. The study finds that users are significantly more concerned when identifiable or sensitive data is involved.

Control and transparency are also limited. Implicit data (e.g., browsing or purchase history) is processed automatically, and users are rarely informed about what is collected or how these signals affect recommendations.

Finally, Zhang et al. (2014) [17] highlights the "privacy–personalization trade-off": more personalized recommendations typically require more data, increasing privacy risk. Users may receive better-targeted content, but at the cost of exposing more behavioural and potentially sensitive information.

3.2 Fairness and Exposure Inequality

Recommender systems often reinforce popularity bias, where already-popular items receive even more visibility while lesser-known creators struggle to gain exposure.

Prior work notes that niche or long-tail items can still constitute a substantial portion of user interest—such as "niche books" accounting for 30–40% of Amazon sales, yet these items remain less likely to surface in recommendation lists.

Popularity can also reflect historical and structural inequalities, meaning that favoring already popular content may disadvantage protected or minority groups; for example, female music artists have been shown to be under-represented and therefore less frequently recommended. Such biases can reduce user autonomy, as preferences may be shaped by what the system promotes, even when users believe they are choosing freely.

Transparency challenges further compound the issue: users generally have little visibility into why specific items are recommended or how recommendation decisions are made. As summarized in Deldjoo et al. (2023) [4], popularity bias is deeply rooted in human cognition, and large-scale recommender systems risk amplifying these imbalances without careful design.

3.3 Psychological and Emotional Harms

Recommender systems can also influence users' emotional states and well-being.

A growing body of evidence links short-form video platforms to compulsive use, mood disturbances, and body-image concerns. Conte et al. (2024) [2] report that adolescents frequently experience "problematic use patterns," including compulsive refreshing and prolonged browsing, even when intending to stop, reflecting an engagement loop reinforced by personalization. Their review highlights that exposure to negative or distressing content often results in further recommendations of similar material, creating "emotional reinforcement loops" that can intensify sadness or distress rather than alleviate it.

Body-image concerns also emerge as a recurrent finding. Conte et al. (2024) [2] note that repeated exposure to idealised physical appearance and lifestyle content is associated with lower self-esteem and higher likelihood of body dissatisfaction among adolescents.

Behavioural evidence from Piao et al. (2025) [14] shows that addicted short-video users tend to consume a narrower range of content, suggesting the formation of emotional or topical echo chambers.

Taken together, these findings indicate that recommender systems may unintentionally reinforce negative emotional states, encourage compulsive usage, and shape users' self-perceptions, especially in vulnerable populations such as adolescents.

3.4 Algorithmic Radicalization and Ideological Drift

Recommender systems optimized for engagement can unintentionally promote extreme or polarizing content. Because emotionally charged material often generates stronger user responses, algorithms may favor it over more neutral alternatives. Haroon et al. (2023) [5] show that YouTube's recommendations "lead users… to ideologically biased and increasingly radical content" across both homepages and up-next suggestions. Similarly, Whittaker et al. report that YouTube "does amplify extreme and fringe content," demonstrating how engagement-driven ranking can reward more sensational material [15].

A second concern is progressive escalation. Users may begin with mild or mainstream content but gradually receive stronger or more extreme recommendations as the system adapts to their engagement patterns. [5]

Finally, recommender systems can narrow users' informational environments by repeatedly surfacing similar content. Rodilosso argues that filter bubbles "can lead to polarization and radicalization of individuals' opinions," as algorithm-driven experiences keep users "confined to our comfort zone" and reduce exposure to opposing viewpoints [13]. This combination of engagement bias, escalation, and narrowing can create pathways through which recommender systems contribute to ideological drift.

4 Mitigation Strategies and Solutions

4.1 Privacy-Preserving Techniques

Given the risks outlined in Section 3, several approaches aim to reduce unnecessary data collection and limit exposure of sensitive information. Federated learning and other forms of on-device personalization train parts of the model directly on user devices, sending only aggregated updates rather than raw behavioural data. This substantially reduces the amount of identifiable information transmitted to central servers and is recognized as a promising privacy-preserving strategy [10].

User-facing controls further strengthen privacy and autonomy. Options to view, modify, or delete stored data—and to disable personalized recommendations—give users clearer control over what is collected. Lightweight explanation tools, such as "Why am I seeing this?" prompts, help users understand how their past interactions influence recommendations. Together, these measures reduce unnecessary data exposure while improving transparency around system behaviour.

4.2 Fairness, Explainability, and System Accountability

Beyond privacy, improving the societal impact of recommender systems requires shifting optimization goals away from maximizing engagement and toward fairness, well-being, and accountability.

Fairness must be treated as a multi-dimensional objective, jointly considered with diversity and novelty, to ensure more balanced exposure across users and creators [4]. Incorporating such objectives helps move systems from keeping users online toward serving them well and supporting equitable creator visibility.

Well-being based optimization can also reduce harmful feedback loops. Systems can detect signs of emotional or ideological narrowing, such as distressing content cycles or strong topical repetition, and adjust recommendations accordingly. Liu et al. (2025) argue that large-scale recommenders "must go beyond personalization to support responsible consumption and foster social good" [9].

Finally, accountability frameworks provide essential oversight. Independent audits of exposure patterns, fairness metrics, and potential emotional or ideological impacts can reveal systemic biases. As Liu et al. (2025) [9] notes, accountability and reporting mechanisms increase transparency and help build public trust. These strategies collectively promote recommender systems that prioritize equitable treatment and long-term user well-being.

5 Team Roles

This project represents an equal collaboration between both team members, with work divided to leverage complementary expertise. Riley Eaton focused on the algorithmic foundations, conducting literature review and writing the complete Algorithmic Background section, researching the evolution from collaborative filtering through matrix factorization to deep neural networks, compiling all citations, and developing presentation slides explaining the technical mechanisms of recommender systems. Aarav Gosalia focused on societal implications, researching and developing content on privacy concerns, fairness and ethical issues, emotional and psychological impacts, algorithmic radicalization risks, and potential solutions, while creating presentation slides for these topics. Riley will present the algorithmic background during the class presentation, while Aarav will present the privacy, fairness, and ethical analysis, with some support from Riley. Both members collaborated on topic selection, overall structure, ensuring smooth integration between technical and societal content, and peer review of each other's work.

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Acknowledgments

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