

# Hybrid Filtering Techniques for Group Recommender Systems: Analysis of Aggregation and Consensus Strategy

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## Abstract

*With the rise of digital platforms, Group Recommender System (GRS) is becoming an indispensable tool across industries such as entertainment, travel, dining, and social networking. This paper investigates hybrid filtering techniques in group recommender systems, specifically focusing on aggregation and consensus strategies that enhance group satisfaction and personalization. Group recommender systems, is essential for collective decision-making on digital platforms, as they encounter unique challenges, including balancing individual preferences to avoid "least misery" scenarios and ensuring user fairness. Thus, this paper first employed a detailed systematic review to identify important research gaps and utilizes the Movie Lens dataset, containing 100,000 ratings across 1682 movies, to evaluate a **K-Nearest Neighbors-Weighted Term Frequency-Inverse Document Frequency (KNN-WTFIDF)** based approach for managing group preferences. Cross-validation ( $k=5$ ) was applied, ensuring balanced training and testing subsets. the analysis reveals gender-based rating patterns, occupation-based rating behavior, and insights into the most and least represented user groups. Findings include a general rating consistency across occupations, with slight variations favoring scientists and retirees, while farmers and unemployed individuals rated the lowest. This work demonstrates how hybrid filtering techniques can enhance satisfaction and fairness in group recommendations, laying a foundation for future research in adaptive group personalization models and robust consensus strategies.*

**Keywords:** Hybrid, Technique, GRS, Aggregation and Consensus.

## 1. Introduction

Group recommender systems (GRS) have emerged to meet the need for shared recommendations in situations where multiple users make joint decisions, such as choosing a movie, restaurant, or vacation destination. Unlike individual recommender systems that cater to one user's preferences, GRS must consider the diverse and sometimes conflicting preferences of multiple users, making the recommendation process complex (Castro, 2019). The importance of GRS lies in its ability to enhance user experience by promoting group satisfaction and reducing the effort of reaching consensus (Meena, & Minz, 2020). The unique challenges of GRS include identifying a balance between individual and group satisfaction, managing conflicts in preferences, and ensuring fairness in recommendations. This is particularly difficult when users have significantly different preferences, as the system must attempt to avoid "least misery" scenarios, where the recommendation may suit most but leave some group members dissatisfied. An understanding of the role and value of GRS sets the foundation for exploring various hybrid filtering techniques that help address these challenges, highlighting the need for effective aggregation and consensus strategies in group settings (Rais, *et al.*, 2024). Group recommender systems (GRS) play a vital role in facilitating decisions among multiple users who share preferences or must compromise on a common choice, such as selecting a movie, restaurant, or travel destination. Unlike individual recommender systems focusing on a user's history, preferences, and behaviors, GRS must account for a diverse set of preferences

and often conflicting opinions among multiple users. This complexity presents unique challenges, making GRS an intriguing area of research within recommendation systems. A well-designed GRS is not merely an amalgamation of individual recommendations but rather an intelligent system that seeks to maximize group satisfaction and minimize the effort required for consensus (Yannam, *et al.*, 2023). As digital experiences increasingly accommodate social interactions, GRS is becoming significant in facilitating shared decision-making. A GRS must consider individual and group preferences to achieve a fair, balanced, and satisfactory recommendation for everyone involved. GRS systems enhance group dynamics by addressing challenges such as preference aggregation, conflict resolution, and fairness, making shared experiences more enjoyable and efficient. The complexity of these challenges, however, emphasizes the importance of advanced techniques such as hybrid filtering, adaptive algorithms, and consensus modeling, all of which are essential in developing a sophisticated and user-friendly GRS (Hui, *et al.*, 2022). This paper developed a Hybrid Filtering Techniques for Group Recommender Systems: Analysis of Aggregation and Consensus Strategy, movie lens dataset was explored and analyzed using Python, the rest of the paper is structured as follows: Section 2.0 Review of Related studies, section 3.0 methodology, Section 4.0 The Importance of Group Recommender Systems in Shared Decision-Making, Section 5.0 Results and Discussion and Section 6. Concludes the research.

## 2. Related Works

The section presents a review of related studies and the challenges unique to group recommender Systems as well as the various research gap presented in table 1.0 as follows.

### 2.1 Challenges Unique to Group Recommender Systems

Developing an effective GRS involves addressing several unique challenges. The first challenge is balancing individual satisfaction with group satisfaction. In GRS, there is often a need to trade off individual preferences for the greater good of the group. This means that the system must find a way to respect each member's preferences to the extent possible while still recommending an option that can satisfy the group as a whole. This balance is not straightforward, as it involves dealing with individual members' divergent preferences, which may vary widely depending on the context (Himeur, *et al.*, 2022). For instance, while selecting a restaurant, one person might prefer vegetarian options, another might want a cuisine they have not tried before, and another might prioritize budget.

A related challenge is managing conflicts in preferences. In many group decision-making scenarios, some preferences are mutually exclusive, meaning that not everyone in the group can be equally satisfied by a single choice. For example, in a group deciding on a movie, preferences for different genres might conflict, making it hard to arrive at a single genre that suits everyone. GRS addresses this through aggregation techniques that aim to balance the desires of each member. However, this approach may not always result in perfect outcomes, especially when preferences are polarized.

Another significant challenge is ensuring fairness in recommendations. Fairness in GRS is about giving each group member's preferences an equitable weight in the final recommendation. Without fairness, there is a risk of disproportionately favoring certain members, which can lead to dissatisfaction and a perception of bias. Fairness is particularly important in diverse groups where members may have differing levels of influence based on their activity level or perceived importance within the group. For instance, in family settings, parents' preferences might inadvertently be given more weight, while children's preferences are

underrepresented. A fair GRS, therefore, must carefully balance influence among group members to create recommendations that respect everyone's input.

## 2.2 Avoiding "Least Misery" Scenarios

One of the goals of a well-designed GRS is to avoid "least misery" scenarios. These occur when a recommendation is chosen that is acceptable to most but highly unsatisfactory to at least one member of the group. For example, a restaurant chosen might suit most group members but leave one person with limited or undesirable options (He, *et al.*, 2016). In such cases, the dissatisfaction of one group member can create negative experiences, undermining the purpose of the recommendation system. To address this, GRS systems often use aggregation methods that minimize the likelihood of extreme dissatisfaction. Approaches such as the "least misery" strategy are employed to select an option that minimizes the dissatisfaction of the least satisfied member. However, while this approach can prevent strongly negative outcomes for certain users, it can sometimes result in overly conservative recommendations that fail to fully satisfy the group's potential interests.

## 2.3 Techniques and Approaches in Group Recommender Systems

To address the above challenges, GRS systems rely on a variety of techniques, primarily based on aggregation and consensus strategies. Aggregation methods in GRS include averaging, least misery, and voting mechanisms. Averaging involves calculating the mean preference of the group, providing a middle-ground option that represents the group's overall taste. While simple and effective in many cases, averaging may not adequately address situations where preferences are polarized or where minority preferences are overshadowed (Harper, & Konstan, 2015). The least misery approach, on the other hand, seeks to minimize dissatisfaction by choosing options that avoid extreme discontent, though it may result in recommendations that are too generalized or compromise group satisfaction. Voting mechanisms in GRS allow group members to vote on options, making the process democratic and more representative of individual preferences. Voting can take various forms, such as rank-based voting, plurality voting, or weighted voting. Rank-based voting involves each member ranking options in order of preference, which the system aggregates to find a consensus choice. Weighted voting can give members with stronger preferences more influence, potentially balancing the group's needs more effectively (Pessemier, *et al.*, 2024). Consensus models go beyond simple aggregation, focusing on negotiation and compromise to reach a solution that better aligns with group preferences. Negotiation models in GRS allow members to express preferences interactively, with recommendations updated based on feedback until a satisfactory option is found. This model can be especially effective in fostering satisfaction, as it involves users in the decision-making process, giving them a sense of control and input. Another approach involves machine learning models that adaptively learn from past group interactions, continuously improving the system's understanding of group dynamics and preferences.

Table 1.0 Summary of Related Studies

References	Model	Objectives	Methodology	Results	Algorithm	What is Missing	Weaknesses	Future Work
<b>Castro, 2019</b>	Multiple models for improving group and context-aware recommendations, including hesitant fuzzy sets, consensus frameworks, and noise management.	Address limitations in current group recommendations, enhance diversity, accuracy, and consensus, and integrate contextual information.	Algorithmic approaches using hesitant fuzzy sets, opinion dynamics, noise management, and context-aware techniques, validated through experiments.	Improved diversity, accuracy, and group satisfaction; enhanced group consensus and effective noise reduction in recommendations.	HGRM, Pre-GROD, GROD, NNM models, and LSACContextCluster for context and consensus-based recommendations.	Validation of diverse datasets, and exploration of real-time applications with evolving group dynamics.	Computational complexity, limitations in balancing individual vs. group satisfaction in varied preference scenarios.	Scalability improvements, integration with advanced machine learning, application in real-time, diverse scenarios, and more domains.
<b>Meena, &amp; Minz, 2020</b>	GA-based multi-expert system for group recommendations (MES-GRS-GA), focusing on consensus building through multi-expert opinions.	Enhance group recommender systems by integrating multi-expert consensus and GA to improve group recommendation accuracy and satisfaction.	A two-phase genetic algorithm (GA) model for consensus and recommendation phases, aimed at maximizing expert utility and minimizing group distance in preferences.	MES-GRS-GA showed increased accuracy and member satisfaction in recommendations when compared to traditional GRS approaches.	Multi-expert system using Genetic Algorithm (MES-GRS-GA), with GA applied in both consensus building and recommendation list formation phases.	Exploration of complex consensus environments, trust-distrust dynamics in consensus, and adaptive expert weighting based on GA.	Limited application in real-world complex consensus scenarios, and fixed weighting for experts, which may not reflect true influence dynamics.	Implementing more complex consensus environments, integrating trust-distrust strategies, and developing adaptive expert weighting to refine consensus outcomes.
<b>Rais, et al., 2024</b>	ITGR framework for food recommendations with overlapping group memberships using fuzzy C-means and DNCF.	To improve group-based food recommendations by addressing challenges of overlapping memberships.	Fuzzy C-means clustering for group formation and DNCF for top-k recommendations.	Outperformed traditional models in group satisfaction, NDCG, precision, recall, and F1-measure.	Fuzzy C-means clustering and DNCF.	Limited flexibility in adapting to dynamic user behaviors and evolving groups.	Oversimplified social dynamics, potentially reducing accuracy.	Explore multi-attention neural networks, user influence on group recommendations, transformer-based NLP, and multi-dataset testing.
<b>Villavicencio, et al., 2018</b>	MAGReS, a multi-agent group recommender system	Improve satisfaction in group recommendations through negotiation over aggregation	Multi-agent system with Monotonic Concession Protocol (MCP) applied in movies and point-of-interest domains	Outperformed aggregation-based methods, increasing satisfaction and fairness across group members	Monotonic Concession Protocol (MCP)	Consideration of user relationships (e.g., friendships) impacting recommendations	Random group selection, reliance on sparse rating matrix	Test with real users use denser datasets, explore new ARP/PRA strategy variants and utility functions
<b>Alvarado et al., 2021</b>	Typology of GRS interaction design strategies	To analyze and categorize design strategies for group recommendation system (GRS) interfaces to improve user experience	A systematic review of 142 papers from ACM, IEEE, and Scopus libraries, coded and analyzed with statistics and thematic analysis	Developed a comprehensive typology of GRS interaction strategies and identified gaps in user inclusion in GRS	None Specified	Lack of diverse user inclusion methods in GRS interface design evaluation	Limited to ACM, IEEE, and Scopus; manual coding with potential biases; included some lower-quality papers	systematic review of interaction design strategies for group recommendation systems. Proceedings of the ACM on Human-

								Computer Interaction.
<b>Balchanowski, et al., 2023</b>	Evaluation of rank aggregation methods in recommendation systems.	To assess how different aggregation methods affect the quality of recommendations.	Used 5 recommendation algorithms and 20 aggregation methods (supervised and unsupervised), with experiments on MovieLens datasets.	Aggregation methods can improve recommendation quality, with supervised methods generally outperforming unsupervised ones.	Rank aggregation methods, supervised and unsupervised.	The impact of parameter tuning was not deeply explored.	Reliance on MovieLens datasets, potential bias in method selection.	Future work will explore a broader range of datasets and a deeper analysis of unsupervised methods' performance.
<b>Ali, et al., 2023</b>	Hybrid Two-phase Group Recommender Framework (HTGF).	To address the problem of users being part of multiple groups with conflicting preferences.	Fuzzy C-means clustering for group membership and Pearson correlation for group formation; Neural Collaborative Filtering (NCF) for recommendation.	HTGF outperformed traditional models in terms of precision, recall, and F-measure, demonstrating better group satisfaction.	Fuzzy C-means clustering, Pearson correlation, and NCF.	Does not explore diverse user characteristics in group formation.	Limited to MovieLens 1M dataset; one evaluation method may not capture all aspects.	Future research will use multi-attention neural networks and transformer-based methods, and test with more datasets.
<b>Alam, &amp; Ali, 2024</b>	Group recommender system with prioritized user activity	Enhance group recommendations via user activity prioritization	Filtering mechanism based on user activity; tested on MovieLens	Prioritizing active users improved precision, recall, and F-scores	User prioritization based on activity levels, similarity measures	Limited to group scenarios; not tested in non-group settings	Only tested on MovieLens; group-based limitations	Extend to individual recommendations, other domains, and incorporate dynamic user preferences
<b>De-Pessemier, et al., 2024</b>	A comparison of group recommendation algorithms for movies with different grouping strategies and recommendation algorithms.	To compare group recommendation strategies, focusing on accuracy, diversity, coverage, and serendipity for movie recommendations.	Combined group members' preferences or recommendations using five algorithms and two grouping strategies; assessed based on accuracy, diversity, coverage, and serendipity.	No single "overall-best" algorithm or strategy; combinations of algorithms and strategies were most effective based on group size and objective.	SVD, IBCF, Hybrid algorithms combined with grouping strategies.	Real-world validation via online experiments with actual users is missing.	Lack of real-world testing limits the generalizability of results.	Future studies will involve online user experiments to validate offline results and test group recommendations in real-world settings.
<b>Pessemier, et al., 2024.</b>	Hybrid travel recommender system for individuals and groups.	Develop a hybrid recommender for travel destinations considering user preferences and feedback.	Hybrid approach with content-based, collaborative filtering, and knowledge-based methods. User testing via	Hybrid system preferred over individual techniques. Positive feedback for group recommendations.	Hybrid algorithm combining multiple techniques.	Explanations for recommendations, nearby location suggestions.	Difficulty gathering metadata and user feedback for travel destinations.	Include explanations, suggest nearby locations, tours, or regions.

			prototype web app.					
<b>Ribas, et al., 2021</b>	An iterated greedy algorithm for scheduling in a parallel blocking flow shop problem with sequence-dependent setup times.	To develop an efficient algorithm for the parallel blocking flow shop scheduling problem to minimize makespan and analyze local search methods.	Performance analysis of iterated greedy algorithms, testing various local search methods and initial solutions to evaluate efficiency.	Variable local search methods improved performance; initial solution significantly influences final outcome.	Iterated greedy algorithm with Swap, Insert, Reassignment, and Permutation local searches.	Does not consider other criteria such as total flow time or tardiness, which are relevant in some industrial environments.	Initial solution quality does not guarantee optimal results; complexity of the problem may require further refinement.	Future research could explore other constraints (e.g., total flow time) and refine the algorithm for better performance in real-world scenarios.
<b>Hossain, et al., 2021</b>	Intelligent Bengali text document classification using GloVe embedding and VDCNN classifier.	To develop a deep learning-based classification method for Bengali text using optimized word embeddings.	Developed two corpora (EC and BDTC), used intrinsic evaluation for embedding models, and applied VDCNN for classification.	GloVe + VDCNN achieved 96.96% accuracy, outperforming other models.	GloVe for embedding, VDCNN for classification, and Embedding Parameters Identification (EPI) for parameter optimization.	Code-mixed datasets and larger class sets were not considered.	Limited by corpus size and low-resource challenges; manual classification required for corpora creation.	Future work could explore transformer-based models, larger datasets, and investigate variable class sizes.
<b>Pérez-Almaguer, et al., 2021</b>	General taxonomy for CB-GRS and hybrid CB-GRS using recommendation aggregation, user-item matching, and aggregation of user profiles.	To propose and evaluate content-based group recommender systems (CB-GRS) and improve upon existing models using hybrid methods.	Developed a general taxonomy for CB-GRS, analyzed three models, and proposed a hybrid model combining feature weighting and aggregation switching.	CB-GRS-Hyb outperformed other models, showing better precision with 1 longer recommendation lists and larger groups.	CB-GRS-Rank, CB-GRS-Match, CB-GRS-AggProf, and a hybrid model (CB-GRS-Hyb).	Collaborative filtering limitations in sparse data scenarios.	Limited by sparse data in collaborative filtering; focus is on binary profiles.	Future research will focus on machine learning for aggregation function selection, matrix factorization, and noise management.

### 3. Methodology

This paper presents a Hybrid Filtering Techniques for Group Recommender Systems: Analysis of Aggregation and Consensus Strategy. The paper first employed a Systematic Literature Review (SLR) approach in conducting comprehensive exploratory learning of relevant existing studies on the field identifying open areas for further research. In the research, a search strategy was developed and utilized to identify unique databases in search of up-to-date, relevant research Articles on Recommender Systems. Google Scholar, ACM Digital Library, Research Gate, IEEE Scopus Indexed platforms and MDPI were primarily used in the search. These sources were Carefully selected due to their extensive indexing of articles on Recommender System and group recommender system. Furthermore, movie lens dataset was explored and analyzed using Python. The MovieLens (Harper and Konstan, 2016) was used for the experimentation of the developed **K-Nearest Neighbors-Weighted Term Frequency-Inverse Document Frequency (KNN-WTFIDF)**. The MovieLens dataset consist of 100,000 ratings and 1682 movie items. The data was generated by 943 users between January 09, 1995 and November 21, 2019. The MovieLens dataset has been used by researchers in many hybrid recommender systems because it is freely available to the public and is considered as standard for this research. There are 19 genres of movies. A movie may belong

to more than one genre. Each user rates at least 20 movies using integer values from 1 to 5 but not all the movies were rated by all users. To represent whether a movie belongs to a specific genre or not, a binary representation of 1 and 0 is used. In order to manage the problem of imbalance data in recommendation, k-fold ( $k=5$ ) cross-validation was used. The training data was divided into 5 equal sized subsets of the dataset. A single subset was used to test the developed KNN-WTFIDF approach and the remaining 4 subsets were used as training data for the developed KNN-WTFIDF approach in the group recommender system.

### 3.1 Enhancing Group Satisfaction and Fairness through Personalization

Personalization in GRS helps improve satisfaction by ensuring that recommendations feel relevant to each member. A GRS that incorporates personalization techniques can adapt recommendations based on the profiles and preferences of individual members, considering past behavior, demographic factors, or contextual data. For example, the system could prioritize options that align closely with each member's preferences in cases where they have a stronger preference or where their participation is critical to group satisfaction. Personalization techniques in GRS may use matrix factorization, clustering, or segmentation to group similar users within a larger group, making recommendations more tailored and likely to appeal to the group (Rais, *et al.*, 2024). However, excessive personalization in a group context can risk creating bias, where certain members' preferences unduly influence the group recommendation. To avoid this, a balance must be struck between personalizing recommendations and maintaining fairness, ensuring that all members' preferences are represented without compromising group harmony. By implementing personalized yet fair recommendations, GRS can enhance user satisfaction and foster a more inclusive decision-making process (De Pessemier, *et al.*, 2024).

### 3.2 The Role of Group Recommender Systems in Digital Platforms

With the rise of digital platforms, GRS is becoming an indispensable tool across industries such as entertainment, travel, dining, and social networking. Platforms that leverage GRS provide a unique experience by allowing groups to make shared decisions easily, thereby enhancing user engagement. For example, in travel planning, GRS enables friends or family members to receive suggestions that align with their collective interests, making the decision-making process simpler and more enjoyable (Bałchanowski, & Boryczka, 2023). Similarly, streaming platforms use GRS to recommend movies or shows that all users in a group are likely to enjoy, enhancing the social aspect of viewing experiences.

### 3.3 Hybrid Filtering Techniques: An Overview

Hybrid filtering techniques combine multiple recommendation approaches, primarily collaborative filtering (CF) and content-based filtering (CBF), to improve the accuracy and relevance of recommendations. In GRS, hybrid filtering plays a crucial role by blending individual preferences with collective group insights. CF typically relies on user interactions or ratings to recommend items to users with similar tastes, while CBF recommends items based on the content characteristics matching the user's profile. By combining these techniques, hybrid filtering aims to mitigate the limitations of each individual method; for example, CF can suffer from cold-start problems with new users or items, whereas CBF can lack the diversity of recommendations (Pérez-Almaguer, *et al.*, 2021). In group settings, hybrid filtering may also incorporate demographic or knowledge-based filtering to account for group characteristics or specific contextual information. This approach is valuable in GRS as it enhances personalization by considering both individual histories and group dynamics. The overview of hybrid filtering techniques in this section provides insights into how these approaches are tailored for group recommendation, emphasizing the flexibility and adaptability that hybrid methods offer in accommodating varied user preferences.

### 3.4 Aggregation Methods for Group Preferences

Aggregation methods in GRS are crucial for synthesizing individual preferences into a collective decision that satisfies the group. Common aggregation techniques include averaging, least misery, and voting mechanisms. Averaging, the most straightforward method, combines individual ratings or preferences by calculating their mean, offering a compromise that tends to favor the majority. However, this method may overlook minority preferences, leading to dissatisfaction. The least misery approach, by contrast, focuses on minimizing the dissatisfaction of the least satisfied member, which can prevent “worst-case” outcomes for certain users but may also lead to overly conservative recommendations (Alvarado, *et al.*, 2021). Voting mechanisms, including plurality or rank-based voting, offer more democratic ways of aggregating preferences by considering each member’s vote equally, yet they can be more complex to implement effectively. More advanced aggregation techniques involve weighted voting or machine learning algorithms that can dynamically adjust preferences based on group characteristics. This section discusses each aggregation method’s advantages and limitations, focusing on how these techniques can impact the group’s satisfaction and the system’s effectiveness in various scenarios.

### 3.5 Consensus Modeling Approaches

Achieving consensus in GRS requires more than simple aggregation; it involves strategies that actively reconcile diverse preferences and foster agreement among group members. Consensus modeling approaches are designed to facilitate mutual satisfaction and can include techniques such as negotiation models, compromise-based recommendations, and machine learning-based consensus strategies (Bałchanowski, & Boryczka, 2023). Negotiation models allow users to express preferences interactively, adjusting recommendations based on user feedback until a mutually satisfactory option is identified. Compromise-based approaches, on the other hand, aim to find a middle ground where preferences are balanced equitably. Recent advancements in machine learning have enabled the development of adaptive consensus models that learn from user interactions and preferences over time, allowing the system to improve its consensus-building capabilities continuously. This subsection explores the importance of consensus modeling for group satisfaction and examines various strategies to align group preferences, emphasizing how consensus-oriented approaches differ from simple aggregation by prioritizing harmony and compromise.

### 3.6 Personalization in Group Recommender Systems

Personalization is essential in GRS to ensure that the recommendations reflect individual preferences while catering to the group’s needs. Personalization in group recommendations involves adapting the recommendations based on individual members’ profiles, preferences, and prior behaviors. This can be achieved through adaptive algorithms that balance group preferences by weighting individual influence according to factors like user engagement, preference strength, or profile similarity (Hui, *et al.*, 2022). Techniques like matrix factorization or clustering can segment users within a group, allowing for more targeted recommendations that consider shared interests without overlooking unique preferences. This section discusses how personalization can improve user satisfaction by making recommendations feel relevant and meaningful to each member, while also addressing the challenges of avoiding personalization bias, where certain users may disproportionately influence group recommendations. The balance between group satisfaction and individual personalization is crucial for effective GRS, as it ensures that each user feels valued and that the system is fair.

### 3.7 Evaluation Metrics for Group Recommendations

Assessing the effectiveness of GRS requires metrics that account for both group and individual satisfaction. Common metrics include accuracy, diversity, fairness, and group satisfaction. Accuracy measures how well the recommended items match the group's collective preferences, while diversity assesses the variety in recommendations, ensuring that a range of interests within the group is represented. Fairness is another critical metric, as it evaluates how equitably the system considers each member's preferences, which is essential in group settings to avoid bias toward specific users (Yannam, *et al.*, 2023). Group satisfaction is often measured through feedback or satisfaction scores, providing direct insights into how well the system meets the group's needs. This section explores each of these metrics and discusses how they can be applied to evaluate the quality of GRS, highlighting the importance of a balanced assessment approach that recognizes the complex nature of group recommendations.

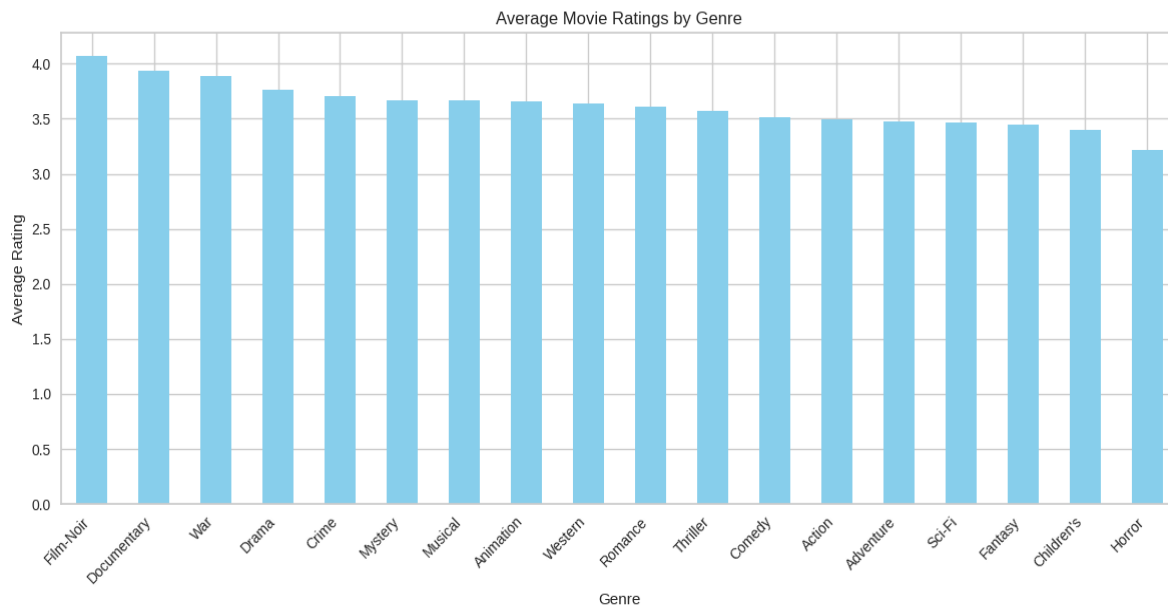
### 3.8 Applications of Hybrid Filtering in Real-world Group Scenarios

Hybrid filtering techniques in GRS are applicable across various real-world domains, where group decision-making is common. Popular applications include travel planning, where groups need recommendations on destinations, accommodations, or activities; dining, where a restaurant must appeal to all group members; and streaming services, where friends or family watch movies or shows together. In each of these contexts, hybrid filtering provides a way to tailor recommendations by combining individual preferences and accounting for group dynamics (Hossain, *et al.*, 2021).

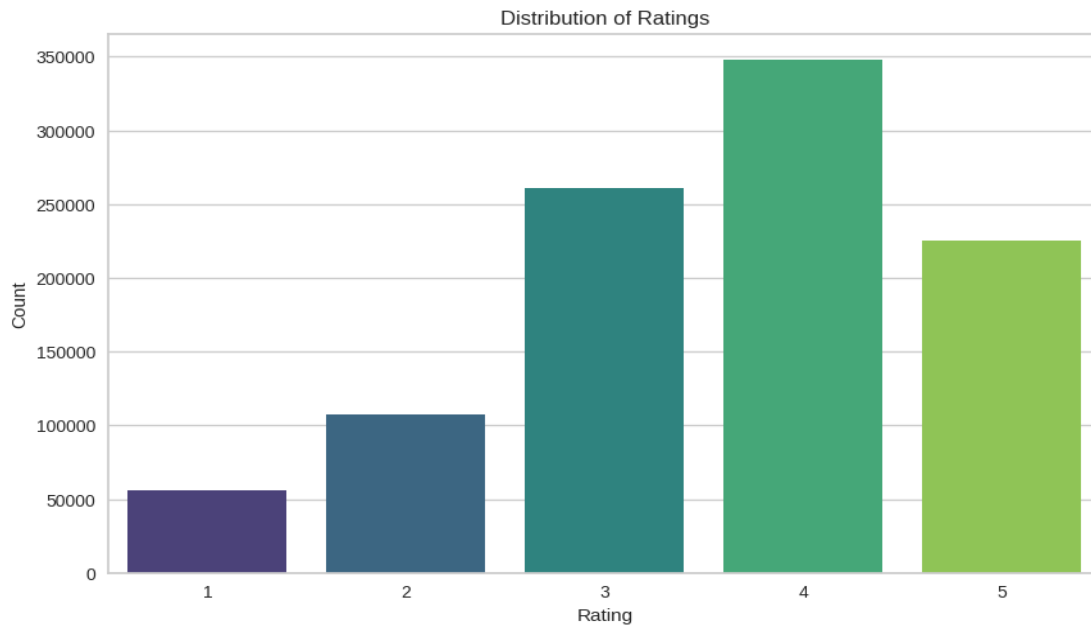
## 4. Results and Discussion

The primary advantage of GRS is its ability to streamline group decision-making, especially in scenarios where joint decisions can be complex and time-consuming. Shared decision-making scenarios are commonplace, and many users expect digital systems to offer tools that cater to both individual and group needs (Huang, *et al.*, 2020). GRS can significantly improve the user experience by suggesting options that consider the preferences of each group member, thus reducing the cognitive load involved in reaching a decision that all members are satisfied with. For instance, in streaming services, a family might use a GRS to pick a movie that balances the preferences of both children and adults, making the selection process enjoyable and efficient. By promoting group satisfaction, GRS encourages users to engage with platforms collaboratively. When a recommendation system successfully aids groups in making decisions, it can strengthen users' connection with the platform, driving loyalty and continued use. This is particularly relevant in sectors like streaming services, social media, hospitality, and travel, where group decisions are often required and where GRS can enhance both convenience and enjoyment. This study employed the potential of hybrid filtering techniques to improve group satisfaction and fairness in recommender systems by effectively integrating personalization, consensus modeling, and aggregation strategies. Through the use of the KNN-WTFIDF approach and the extensive Movie Lens dataset, we demonstrated how these hybrid methods address unique challenges in group recommender systems, including the management of diverse preferences and avoiding "least misery" outcomes. Findings indicate consistent rating behaviors across different occupations and an inclination toward higher ratings among specific demographic groups, which can inform tailored approaches in group recommendations. This research offers valuable insights for designing more inclusive and balanced group recommender systems on digital platforms, paving

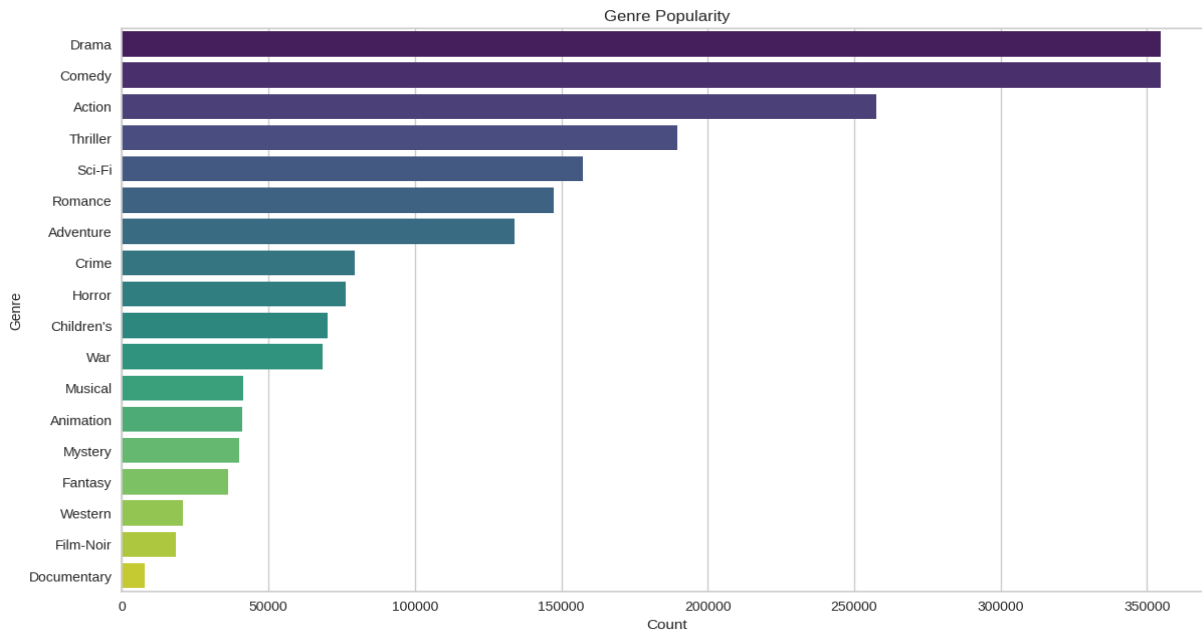
the way for further advancements in adaptive and scalable group recommendation methodologies. The bar chart in Figure 5 illustrates gender-based rating trends across all categories (1–5). Key findings include: Male users (M) show a higher count than female users (F), indicating a slightly harsher rating tendency among males. Male users consistently outnumber female users, showing a higher engagement in providing moderate ratings. Male users have the highest rating counts, suggesting greater overall participation. Rating 4 has the highest number of ratings from both genders. While Highest Average Ratings: Retired individuals and scientists exhibit the highest average ratings, slightly above 3.5, implying a generally positive disposition toward the rated content. Unemployed users and farmers provide the lowest average ratings, marginally below 3.5, suggesting a more reserved rating style in these groups. Average ratings are clustered around 3.5 across most occupations, reflecting a standard rating behavior across job types. College/graduate students and "other or unspecified" users are most prevalent, each with over 120,000 entries. Executive/managerial, academic/educator, and technician/engineer professions are prominent, with entries ranging between 50,000 and 80,000. Farmers, homemakers, and tradesmen/craftsmen are underrepresented, with counts below 10,000. In conclusion, the dataset is dominated by college students and unspecified users, while farming, homemaking, and trades are the least represented categories. The distribution suggests that recommendations might need to adapt to higher-frequency occupations to cater to the majority user base effectively.



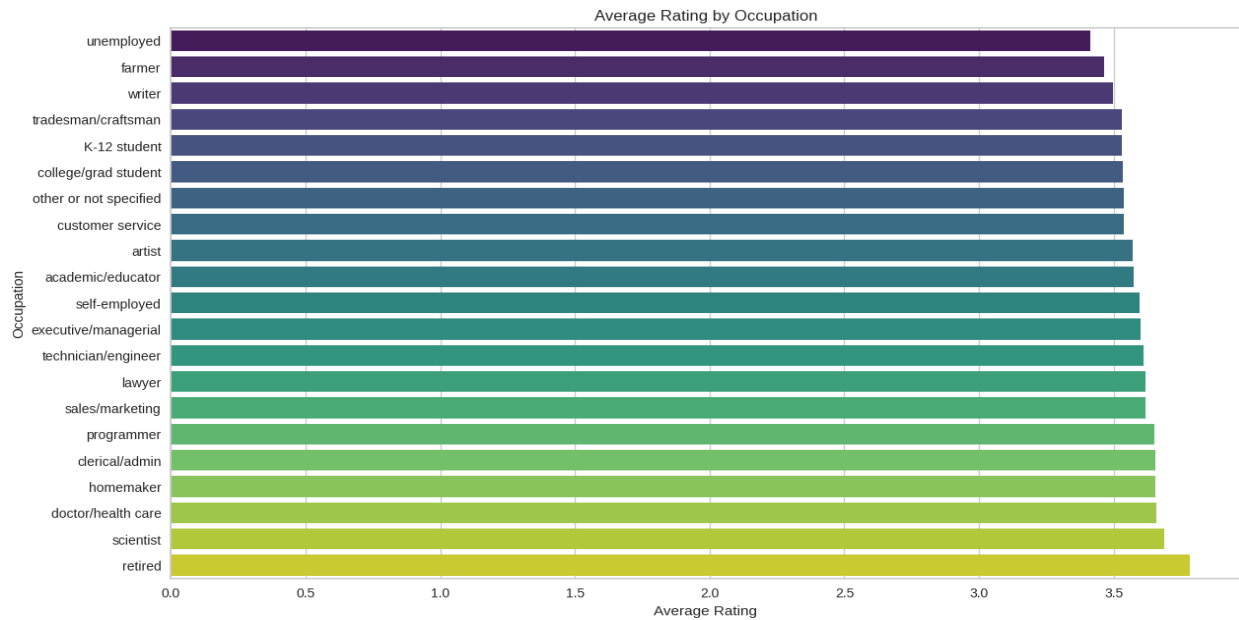
**Figure 1:** The bar chart shows the average movie ratings by genre. Film-Noir has the highest average rating, followed by Documentary and War. Horror has the lowest average rating. Most genres have average ratings between 3.0 and 4.0.



**Figure 2:** The bar chart shows the distribution of ratings from 1 to 5. The most common rating is 4, followed by 3, 5, 2, and the least common rating is 1.

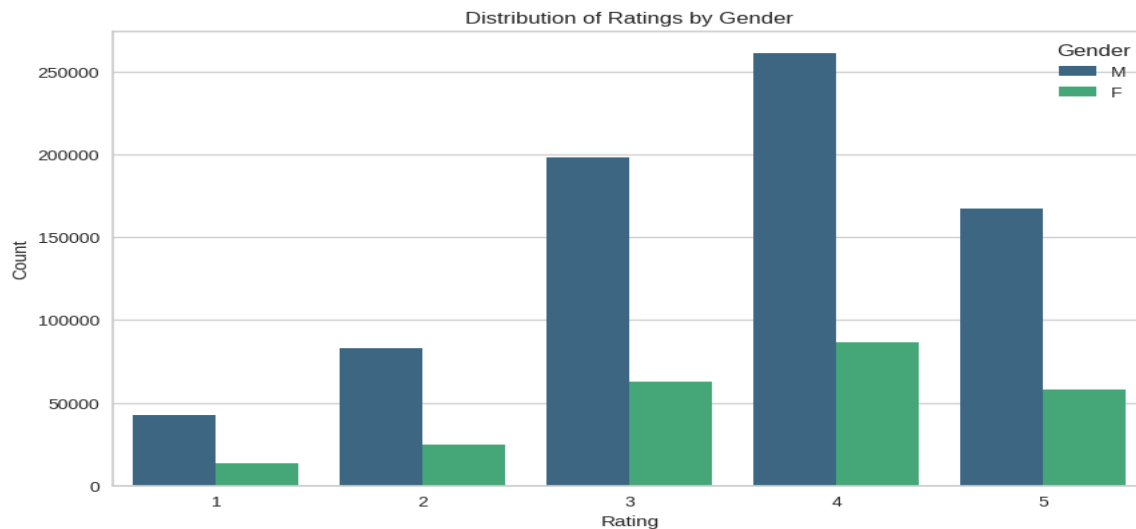


**Figure 3:** The bar chart displays the distribution of users across different occupations. Key points include: Most Common Occupations: College/grad students and users in the "other or not specified" category have the highest counts, each exceeding 120,000. Other Notable Occupations: Executive/managerial, academic/educator, and technician/engineer are also prevalent, with counts ranging from around 50,000 to 80,000. And the Least Common Occupations: Farmers, homemakers, and tradesmen/craftsmen have the lowest counts, each below 10,000. Finally, college/grad students and unspecified occupations dominate the user base, while farming, homemaking, and trades are the least represented.



**Figure 4:** The bar chart shows the average ratings given by users based on their occupation.

Key observations include: **Highest Average Ratings:** Retired individuals and scientists give the highest average ratings, both slightly above 3.5. **Lowest Average Ratings:** Unemployed users and farmers give the lowest average ratings, slightly below 3.5. **General Trend:** Most occupations have average ratings clustered around 3.5, indicating a general consistency in rating behavior across different job types. Finally, while there are slight variations, the average ratings are fairly consistent across different occupations, with retired individuals and scientists giving marginally higher ratings.



**Figure 5:** The bar chart displays the distribution of ratings by gender, with ratings ranging from 1 to 5.

The chart reveals the following insights: For rating 1, male users (M) have a higher count compared to female users (F). For rating 2, male users again have a higher count than female users. For rating 3, male users have a significantly higher count than female users. For rating 4, male users have the

highest count, followed by female users. For rating 5, male users have a higher count than female users. Thus, male users tend to provide more ratings across all categories compared to female users, with the highest number of ratings given for rating 4 by both genders.

## 5. Conclusion

This study developed a hybrid filtering technique in group recommender systems, emphasizing the balance between personalization and consensus strategies. The developed KNN-WTFIDF approach and analyses based on the MovieLens dataset, the study observed a significant gender- and occupation-based trends. The study discovered that Male users are more active in ratings across all categories, and occupation influences rating patterns, with retired individuals with scientists providing higher ratings on average. The results proved that group recommender systems can benefit from tailored aggregation and consensus methods to account for varying user demographics. Future work will focus on optimizing hybrid filtering techniques to improve adaptability and fairness in recommendations, particularly by addressing data representation imbalances and refining personalization features. The future of hybrid GRS involves several promising directions, including advancements in machine learning, real-time personalization, and privacy-preserving techniques. Emerging technologies like deep learning and reinforcement learning could enhance GRS by enabling more dynamic and adaptive recommendations that evolve with user interactions. Real-time personalization could further improve user experience by adapting recommendations as group preferences change. Privacy-preserving techniques, such as federated learning, may also play a critical role in addressing privacy concerns while still allowing for accurate recommendations.

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