Unravelling Filter Bubbles in Recommender Systems: A Comprehensive Review

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Abstracts: The prevalence of filter bubbles in recommender systems has raised concerns about the potential impact on user experiences and information exposure. This systematic literature review aims to deliver a thorough analysis for the study conducted on filter bubbles in recommender systems and its implications for user experiences and information exposure. Through a thorough bibliometric analysis using VOSViewer, the research landscape is mapped, influential authors are identified, and recurring themes are examined. The review delves into theoretical frameworks, empirical studies, and algorithmic approaches to highlight the challenges and opportunities associated with detecting and mitigating filter bubbles. Key findings encompass the identification of filter bubbles, their impact on user behavior, and proposed solutions. Additionally, an analysis of datasets used in this context is presented, alongside notable solutions developed to address filter bubbles in recommender systems. The review investigates the unresolved obstacles in the domain of filter bubbles within recommender systems. The review also explores potential future directions and solutions to mitigate filter bubbles, underscoring the significance of understanding their implications for user decision-making and information diversity. By contributing to the ongoing discourse on recommendation systems, this research offers valuable insights to researchers, practitioners, and policymakers seeking to address the filter bubble phenomenon and enhance user experiences in the realm of recommender systems.

Keywords: Filter Bubble, Recommendation, Recommender System, User Experience.

1. INTRODUCTION

The amount of data and information people have access to has increased by an unheard-of amount during the previous two decades. Nowadays the way in which people consume information has changed dramatically. Thanks to advances in interactive communication technology, people can now access vast amounts of information on anytopic with just a few clicks. Additionally, the rise of social media platforms in the past decade has transformed society in ways that were previously unimaginable. Since interactive communication technology has advanced and the Internet is now widely accessible, it has emerged as a significant source of information (Raza and Ding 2022). Users are no longer restricted to a single source, and instead, have a wealth of options at their fingertips.

However, with so much information available, users can find it overwhelming to locate the relevant and accurate data they need. To address this issue, Recommender Systems have emerged to meet user's interest. In this age of information explosion, recommender systems are becoming more and more crucial for providing personalised information filtering services (Rendle 2012). Recommender systems are automated systems that filter different entities on the internet, such as movies, music, products, news, and more. In the midst of the information explosion, they play a crucial role in assisting users in finding the information they require.

Recommender Systems have become a popular area of research in recent years, as there has been rapid growth in the development of systems that can provide users with customized recommendations based on their preferences.

A recommender system is a software system that uses algorithms to analyse data and make personalized recommendations to users (Joeran et al. 2018). They are frequently used in social networking, e-commerce, and content platforms to assist users in finding new goods, services, or material that they would enjoy.

As the field of recommender systems continues to grow, a number of challenges have been identified and discussed in the literature (Dokoupil 2022; Sayed et al. 2022). Among the most discussed issues in recommender system research are the problems of Cold Start, long Tail and sparsity, which have been examined in several studies (Tahmasebi et al. 2021; Ali et al. 2022). The scalability of recommender systems has also been addressedby some researchers (Wu et al. 2022; Sardianos et al. 2020).

Moreover, the privacy and security concerns associated with the use of recommender systems have become a significant area of focus for researchers a (Shakil et al. 2022). The sensitive nature of user data collected by these systems, including browsing history, purchase history, and personal preferences, has raised concerns about the potential for privacy breaches and security threats. In order to ensure that recommender systems are used safely and responsibly, researchers are working to develop better privacy and security measures, such as data encryption and anonymization techniques, to protect user information. Overall, the identification and resolution of these issues is crucial to the ongoing development and success of recommender systems in a wide range of applications.

One of the significant issues that have been identified in Recommender Systems is the problem of Filter Bubble.It is a phenomenon where users are suggested items that align with their existing preferences and interests, limiting their exposure to new or diverse information. In other words, the system creates a "bubble" around the user, restricting them to a narrow range of items and ideas. This has the potential to be a significant drawback of using recommender systems as it can lead to users missing out on discovering new and exciting items that they would have otherwise been interested in.

Moreover, the Filter Bubble problem can further contribute to the creation and reinforcement of user biases, leading to the development of echo chambers. Echo chambers are where individuals only encounter information that confirms their pre-existing beliefs, leading to the development of a narrow worldview. This can have adverse effects on the society as it can lead to the formation of extreme opinions and an inability to consider other perspectives. As a result, it is crucial to address the Filter Bubble problem in recommender systems to make surethat users are exposed to a variety of concepts and products, fostering a wider perspective and a more inclusive society.

2. BIBLIOGRAPHIC ANALYSIS

This comprehensive synthesis and organization of the most recent contributions to the filter bubble thesis is the goal of this systematic literature review. The filter bubble phenomenon has been widely discussed in the literature as a potential drawback of recommendation algorithms and their effect on users' exposure to a range of ideas and content; while some researchers claim that there is no such issue with filter bubble and there should be no discussion regarding it. As such, this paper will explore current research on filter bubbles, including its various aliases like echo chambers, to shed light on its effects and potential solutions.

To achieve this objective, a comprehensive bibliometric analysis was performed. The analysis involved the utilization of a specialized bibliometric tool known as VOSViewer. With the assistance of this tool, a network visualization map was created, showcasing the interconnections among the authors of the included papers. Additionally, a word map was generated, focusing on the abstracts and titles of the papers under review. The wordmap is shown in Figure 1. We can see that in the map words which are closer to the ‘filter bubble’ term, such as social media, diversity, echo chambers, etc. These visual representations offer valuable insights into the patterns and trends within the literature, enhancing the overall understanding of the research landscape surrounding filter bubbles in recommender systems. In addition, we have created a word cloud (refer to Figure 2) based on the abstracts of the papers included in our study. This visual representation provides insights into other significant terms related to the filter bubble problem. By analysing the word cloud, we can gain a broader understanding of the relevant concepts and themes associated with the filter bubble phenomenon.

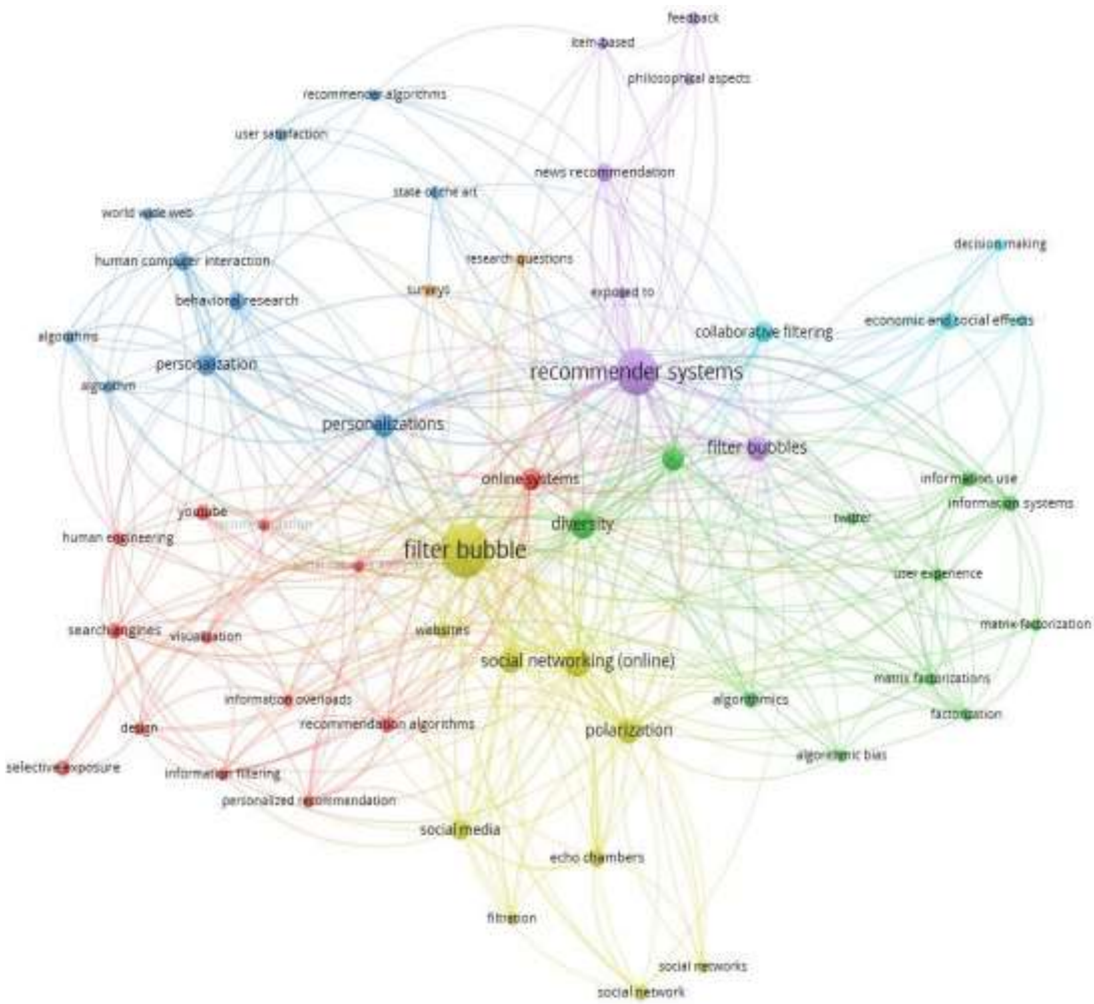

Fig 1: Word Map of Abstracts and Titles of the papers included in this survey.

Fig 2: Word Cloud of Abstracts of the papers included in this survey.

The Methodology used in this work is motivated by (Raza and Ding 2022)'s review on news recommender systems. To ensure a thorough and unbiased analysis of the literature on filter bubbles and recommender systems, precise search methods, scope, and objectives were established. The goal was to maintain objectivity throughout the review process and minimize any potential biases in the selection of relevant literature.

To identify and select relevant literature, we used a set of bibliographic databases including ACM Digital Library, Elsevier, IEEE Xplore, Scopus and Springer. To ensure a thorough search for related papers, we also used a number of scholarly search engines, including Google Scholar, DBLP, Research Gate, and Web of Science. In order to find pertinent titles and abstracts that might have been overlooked during the original search, we also looked through journal transactions and conference proceedings.

Overall, this multi-faceted approach ensured that a diverse range of literature on filter bubbles and recommender systems was identified and included in our survey. By incorporating various search methods and databases, we were able to create a thorough and objective assessment of the current state of research on this subject.

To search for relevant literature on the filter bubble and its association with recommender systems, a Boolean search query was used. The query used was ("Filter Bubble") AND ("Recommender Systems") OR ("Recommendation Systems") OR ("Recommendations"). Additionally, a similar query was used, replacing "Filter Bubble" with "Echo Chamber".

2.1 Inclusion Criteria:

To ensure that the selected papers were appropriate and relevant to the research topic, a set of inclusion criteria was established. These criteria included the requirement for papers to be written in English, as well as their perceived value and applicability to the matter. Moreover, the scope of the review was limited to journal papers and conference papers, as they are typically considered to be more scholarly and provide substantial research contributions. This approach aimed to ensure a comprehensive and rigorous examination of literature while maintaining a focus on high-quality sources within the field of study.

2.2. Exclusion Criteria:

This systematic review paper focused specifically on peer-reviewed journal papers and meeting papers, while ignoring non-journal sources such workshop papers, papers that include presentation slides, and grey literature.

This approach was taken to prioritize scholarly and extensively reviewed sources, ensuring the reliability and credibility of the included literature.

2.3. Contribution Of This Research Work:

This research endeavors to emphasize the significance of comprehending the intricate nature of filter bubbles and their influence on users' behavior, attitudes, and decision-making processes. By conducting an extensive analysis of the most recent contributions to the filter bubble thesis, this paper aims to make a valuable contribution to the ongoing exploration of recommendation systems and their role in shaping users' online experiences. Through this analysis, the study endeavors to uncover valuable insights that can enhance our understanding of how filter bubbles operate and their profound impact on user engagement and information consumption in digital environments. The findings derived from this study hold the potential to inform the development of more effective strategies for mitigating the negative consequences associated with filter bubbles and promoting a more diverse and balanced online information ecosystem.

The structure of the paper is to give a clear and thorough comprehension of the research done on the filter bubble and recommender systems. In Section 3 Related work of the previous surveys in Filter bubbles is being discussed. In Section 4, background of recommender systems and filter bubble is discussed. Also, a comprehensive overview of commonly used datasets for this research is provided. In Section 5, we will examine the outcomes and implications of this study, focusing on the identification and mitigation of filter bubbles. Additionally, we will explore noteworthy approaches and solutions proposed to address the issue of filter bubbles in recommender systems. Section 6 discusses the open challenges in the field of filter bubbles and recommender systems. In Section7, future work in this field is discussed, which can help researchers to identify new areas of research and develop more effective solutions. Finally, in Section 8, the survey concludes with a summary of the key findings and contributions made in this paper.

3. RELATED WORK

To learn more about what is currently known about the Filter Bubble, we examined previous surveys to determine their scope and coverage. (Bruns 2019)'s analysis challenges the evidence supporting the "Filter Bubble" hypothesis, stating that users have a tendency to have a more varied and centrist media diet than non-users. Despite this, the ideas nevertheless influence society structures, media and communication channels, and user experiences. In the mainstream media and political discussions, the employment of filter bubble and echo chamber rhetoric has produced a perceived impact that concerns researchers and policymakers, even if the existence of filter bubbles isinconclusive.

(Dahlgren 2021) clarified Pariser's filter bubble thesis, which has two interconnected aspects: technological and societal. Personalization algorithms narrow users' available content based on past choices, while also impacting broader societal implications such as political processes and democratic values. Understanding the filter bubble phenomenon at both levels is crucial to fully comprehend its impact on individuals and society. (Amrollahi 2021) proposed an integrated solution to help social network users avoid filter bubbles. The researchers conducted a comprehensive literature review and designed a tool that focuses on user data collection, personalized content delivery, filter bubble detection, and user feedback. By broadening the range of material and minimising polarisation, the suggested approach has the potential to lessen the detrimental effects of filter bubbles on users of social networks.

(Terren and Borge 2021) reviewed 55 papers that looked into the occurrence of echo chambers on social media in 2021. While there is no clear consensus on the existence of echo chambers, many studies suggest that they do exist to some extent. The authors noted that discrepancies in findings may be due to variations in how echo chambers are defined and operationalized across studies. The review provides a comprehensive account of the literature on echo chambers in social media and highlights the need for further research to better understand this phenomenon and its implications.

Additionally, (Miller et al. 2021) carried out research to examine how digital echo chambers and filter bubbles are used in nature conservation practices. A review of the literature and a computerized expert survey of German conservationists were part of the study. The results of the study indicate that these phenomena are already being studied in connection with conservation problems, particularly climate protection and natural conservation practice. However, it was shown that they provide more risks than benefits for communicating about wildlife protection. The study also revealed a lack of understanding of the specific mechanics involved in digital echo chambers and filter bubbles. As a result, there is a considerable need for research in the strategic assessment and management of these phenomena in natural conservation practice.

(Michiels et al. 2022) proposed an operationalized definition of the technological filter bubble, characterized by a gradual decrease in content variation throughout time. They reviewed previous research and observed that diverse interpretations of the concept made it challenging to compare and synthesize findings. The authors emphasize the importance of a well-defined concept to facilitate future research and highlight the need for a multidisciplinary approach to understanding filter bubbles involving technological, social, and political factors.

In Table 1, a brief summary of recently published surveys on the topic of filter bubbles is provided. It is important to note that these surveys do not focus on recommender systems, but rather on various aspects of filter bubbles inthe context of online media and social networks.

Table 1: Brief summary of Recent Published Filter Bubble surveys.

Paper Ref.	**Title of Survey Paper**	**Related To Recommender Systems?**
(Bruns 2019)	*"Filter bubble"*	NO
(Kuehn and Salter 2020)	*"Assessing Digital Threats to Democracy, and Workable Solutions: A Review of the Recent Literature"*	NO
(Dahlgren 2021)	*"A critical review of filter bubbles anda comparison with selective exposure"*	NO
(Amrollahi 2021)	*"A Conceptual Tool to Eliminate Filter Bubbles in Social Networks"*	NO
(Terren and Borge 2021)	*"Echo Chambers on social media: ASystematic Review of the Literature"*	
(Miller et al. 2021)	*"The potential relevance of digital echo chambers and filter bubbles for nature conservation practice"*	NO
(Michiels et al. 2022)	*"What Are Filter Bubbles Really? AReview of the Conceptual and Empirical Work"*	NO
This Paper	*"Unravelling Filter Bubbles in Recommender Systems: A Comprehensive Review"*	YES

This systematic review paper aims to provide a complete summary of the latest research on the filter bubble phenomenon in recommender systems, including its various aliases, to examine its effects and potential solutions. The paper will carefully analyse the existing literature on filter bubbles in recommender systems and provide recommendations for mitigating their negative effects in different contexts. The paper aims to contribute to the ongoing research on filter bubble in recommender systems and their impact on users' experiences online.

4. BACKGROUND

4.1. Recommender Systems

Recommender systems are software tools that provide personalized recommendations to users based on their previous interactions with the system. Recommender Systems suggest a wide range of items, including movies, products, travel destinations, advertisements, and news articles. The user's activity history is used to infer their implicit or explicit preferences. Implicit preferences can be inferred by analysing the user's browsing history, shopping behaviour, clicked links, and cookies without directly soliciting feedback. Alternatively, explicit feedback can be collected by asking users to rate or provide feedback on the recommendations they receive. Content-based filtering, collaborative filtering, and hybrid recommender systems are a few examples of the various types of recommender systems. A detailed diagram showing types and subtypes of recommender systemsis shown in figure 3.

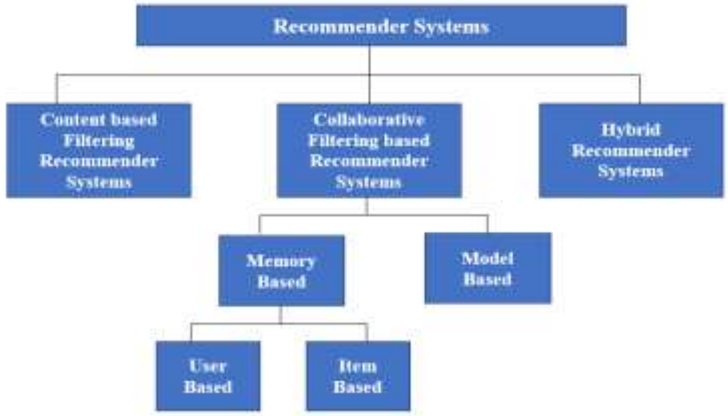

Fig 3. Recommender Systems and Its types

The first research paper on Recommender Systems was published in 1998 by Giles et al. as part of the CiteSeer project (Joeran et al. 2018). Since then, a multitude of articles have been published covering various recommendation approaches. At first, the primary focus of Recommender Systems was to provide "accurate" results, indicating how precise a recommendation is concerning a specific user. Nevertheless, as Recommender System research expanded, a more comprehensive perspective on recommendation benefits beyond mere accuracyarose in the literature (Herlocker et al. 2004; Smyth and McClave 2001).

In their paper,(McNee, Riedl, and Konstan 2006) argued that the narrow focus on accuracy as the primary goal of Recommender Systems has had detrimental effects on the field. They claim that sometimes the recommendations that are most accurate based on accepted measures are not the advice that consumers would find most helpful. As time passed, this viewpoint gained traction, and Novelty and Diversity, along with accuracy, became important metrics to measure how good the recommendations provided by a Recommender System are for its users.

Novelty refers to the ability of a Recommender System to recommend items that users may not have encountered before. Diversity, on the other hand, pertains to the variety of items recommended to users. Recommender Systems that provide diverse recommendations allow users to explore new areas of interest, leading to a better overall userexperience.

In conclusion, while accuracy is still an important metric, the focus has shifted towards providing recommendations that are not only accurate but also diverse and novel. These metrics are essential in determiningthe usefulness of a Recommender System and enhancing user satisfaction.

4.2. Filter Bubble

The term "Filter Bubble" was originally introduced by Eli Pariser, an Internet activist and author, in his book titled *"The Filter Bubble: What The Internet Is Hiding From You"* (Pariser, Eli, 2011). He described the term as:

“The new generation of Internet filters looks at the things you seem to like—the actual things you’ve done, or the things people like you like—and tries to extrapolate. They are prediction engines, constantly creating and refining a theory of who you are and what you’ll do and want next. Together, these engines create a unique universe of information for each of us—what I’ve come to call a filter bubble—which fundamentally alters the way we encounter ideas and information (Pariser, Eli, 2011).*”*

According to [69], these variations in search results may be the consequence of the algorithmic personalisation provided by search engines like Google. He suggests that this creates a "personalized universe of information" for each user, also known as a filter bubble, which can differ significantly from one user to another.

The concept of the "Filter Bubble" describes the risk that personalization algorithms in online services can create a narrowing effect on the information and viewpoints that users are exposed to. This can result in users being presented with information that confirms their existing beliefs, without encountering diverse perspectives. The issue was first identified in 2009, as search engines like Google started to use personalization to tailor search results to individual users based on their past behaviours, preferences, and other factors. As a result, users may receive different search results than others who have searched for the same query, leading to potential information silos and a lack of exposure to alternative viewpoints (Felfernig et al. 2015).

While the consequences of skewed information experiences are often referred to as "echo chambers" (McNee, Riedl, and Konstan 2006) in the media communication field, the term "filter bubbles" is more commonly used in the information retrieval community. Essentially, filter bubbles are self-reinforcing systems that limit users' exposure to diverse ideas, beliefs, or content (Karlsen et al. 2017), thereby excluding them from different perspectives. As a result, users are recommended only those items that align with their existing preferences, which can lead to a problem of limited perspective. This effect can be seen as a potential drawback of using recommender systems, as users may miss out on discovering new and exciting items that they would have otherwise been interested in.

It is essential to acknowledge that not all recommender systems are designed to create filter bubbles, and not all of them are harmful. Additionally, whether or not a filter bubble leads to isolation depends on the specific context and how the system is used. For example, if a recommendation system is used to help users discover new content that is similar to what they already like, it could be seen as a positive feature. On the other hand, if the system is used to provide users with news or information, a filter bubble could lead to a lack of exposure to diverse viewpoints and reinforce existing biases. Therefore, it is important to understand the potential consequences of filter bubbles and develop strategies to mitigate their negative effects.

The filter bubble effect in business creates the "Matthew effect" among popular items, in which products and information that do not meet the long tail hypothesis cannot be suggested, affecting diverse product sales and corporate success (Fleder and Hosanagar 2009; Lee and Hosanagar 2014).

The concept of filter bubble has been widely discussed in the literature in the context of internet personalization, but its impact on recommender systems has not been extensively studied (Z. Gao et al. 2022). Despite its potential implications for Recommender Systems, research on filter bubble in this area is still relatively new and has gained significant attention from the research community in recent years, particularly in relation to social network-related systems (Spohr 2017).

4.3. Datasets

To study the impact of filter bubbles in recommender systems, researchers can use a variety of datasets, depending on the research question and focus of the study. One type of dataset commonly used is user-item or item-item interaction data, which captures users' historical interactions with various items such as movies, music, news articles, and other types of content. This type of data provides insight into how users engage with different items and how the recommender system can use this information to make personalized recommendations.

Another type of dataset that can be used is content-based data, which includes text from news articles, features of a product, or the genre of a movie. This type of data allows researchers to examine how the recommender system uses the characteristics of the content to provide recommendations. For example, a news recommender system may recommend articles on a specific topic that the user has previously shown an interest in.

If the focus of the study is on social media, social network data can be used to study the impact of social connections on the formation of filter bubbles. This type of data includes information about a user's connections and interactions on social media platforms and can be used to analyse how the recommender system tailors recommendations based on the user's social network.

In addition to the above types of datasets, demographic data, sentiment analysis data, and user feedback data can also be used. Demographic data includes information about the user's age, gender, and location, while sentiment analysis data measures the emotional tone of user feedback. User feedback data includes information about user ratings, reviews, and comments, which can help to assess the effectiveness of the recommender system.

Overall, the choice of dataset depends on the specific research question and focus of the study, and different types of datasets can provide valuable insights into how filter bubbles are formed in recommender systems. Later in thissection, we will explore some examples of these datasets.

4.3.1. MovieLens Dataset. The MovieLens Dataset is a collection of movie ratings from the MovieLens website, a platform for movie recommendations. It is the most common dataset used in making movie recommender system. First released in 1998, it describes users' expressed preferences for movies in the form of tuples, which contain a user's rating (from 0 to 5 stars) for a movie at a particular time. The dataset is maintained by GroupLens, a research group at the University of Minnesota. There are five versions of the dataset: "25m," "latest-small," "100k," "1m,"and "20m." In each version, the movies data are joined on the "movieId" column.

The "25m" version is the latest and recommended for research purposes. The "latest-small" version is a small subset of the latest version that is updated over time by GroupLens. The "100k" version is the oldest and smallest dataset, containing only demographic data. The "1m" version is the largest MovieLens dataset, also containing demographic data. Finally, the "20m" version is one of the most widely used datasets in academic papers, along with the "1m" dataset.

4.3.2. Douban Dataset. Douban is a social networking platform based in China that is renowned for hosting the most extensive review database of Chinese movies, music, and books. This platform is an excellent source of information for researchers as it contains a plethora of user behaviour data such as user ratings, user reviews, and resource descriptions. Furthermore, Douban also includes social tags marked by users for resources, which can provide insights into users' perceptions and preferences. These social tags are ranked according to the number of users who use them, providing a valuable indicator of the popularity of different resources on the platform. As such, Douban is a valuable resource for researchers looking to analyse user behaviour and preferences in the context of Chinese media and entertainment.

4.3.4. Amazon-Book Dataset. The Amazon-Book dataset, also referred to as Amazon Book Reviews dataset, is an extensive collection of reviews and ratings for books published by Amazon through its AWS program. It includes metadata on books, such as author, title, category, and descriptions, as well as customer reviews containing helpfulness votes, ratings, and text reviews. The dataset spans over two decades, from 1995 to 2018, and provides a wealth of information for researchers analysing the filter bubble problem. By studying the reviews and metadata contained in the Amazon Book Reviews dataset, researchers can gain insights into the types of books and topics that various user groups find appealing. Furthermore, analysing the language and sentiment used in these reviews can shed light on how different user groups self-select into specific content and the degree to which users are exposed to diverse viewpoints. This information is useful for researchers seeking to understand the filter bubble phenomenon in recommender systems.

4.3.5. News Category Dataset. The news category dataset is a collection of over 210,000 news headlines published on the progressive news website HuffPost between 2012 and 2022. This dataset, which is one of the largest news datasets available, can be useful for investigating the filter bubble phenomenon in news recommendation systems and serves as a benchmark for various computational linguistic tasks. The dataset was first compiled in 2018, after HuffPost stopped maintaining an extensive archive of news articles. Of the 210,000 news headlines, around 200,000 are from the years 2012 to 2018, while the remaining 10,000 are from the years 2018 to 2022.

The datasets mentioned above are commonly used for studying both recommender systems and the filter bubble problem. However, some researchers choose to take a different approach by creating profiles on platforms like Google News and observing the recommendations made over a specific period of time. This method allows researchers to analyse how personalized the recommendations are and how they are tailored to individual user preferences.

Furthermore, social media data is also used by some researchers to analyse the filter bubble problem. For instance, Twitter data can be used to study how users engage with news and information on the platform, and the extent to which they are exposed to diverse viewpoints. By analysing user behaviour on social media platforms, researchers can gain insights into the types of content that users are exposed to, and the factors that influence their content preferences.

In the following section, we will explore the findings and indications of the filter bubble problem in recommender systems.

5. FINDINGS & INDICATIONS

Recommender Systems have the potential to create or dissolve a filter bubble, ultimately shaping the openness or closedness of the internet. However, the concept of filter bubbles is still a relatively new area of research, which has led to limited studies. As illustrated in Figure 4, the number of studies conducted on the "Filter Bubble in Recommender Systems" has increased significantly in recent years, indicating a growing interest in this area of research.

This trend highlights the importance of understanding the role of recommender systems in shaping the filter bubble phenomenon. As such, it is imperative to examine the characteristics and workings of recommender systems and filter bubbles holistically to understand how they interact with one another. By doing so, researchers can identify potential solutions to mitigate the negative effects of filter bubbles and enhance the positive aspects of recommender systems in shaping the internet landscape.

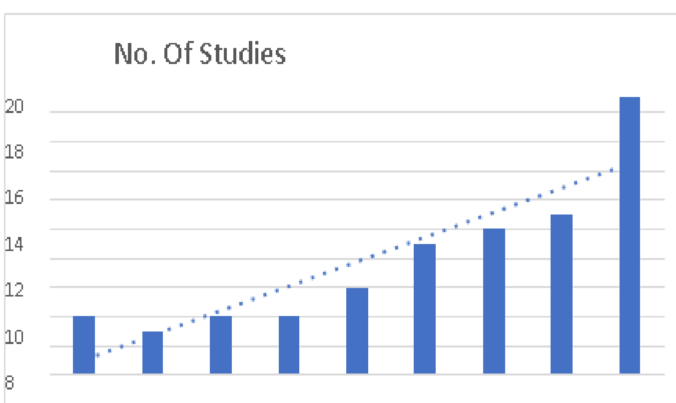

Fig 4: Number of studies over the years

The existing literature on Filter Bubbles in Recommender Systems is divided into two main streams. The first stream primarily focuses on the identification, formation, and measurement of Filter Bubbles in Recommender Systems (Sun et al. 2022). The researchers in this stream investigate various methods to detect Filter Bubbles, their formation, and the factors influencing their size and intensity. They also examine how users are exposed to and affected by Filter Bubbles in Recommender Systems. Additionally, the researchers in this stream study the metrics and evaluation techniques used to measure the effectiveness of solutions for mitigating Filter Bubbles.

On the other hand, the second stream of research is focused on developing solutions to mitigate Filter Bubbles in Recommender Systems (Sun et al. 2022). The researchers in this stream propose and evaluate various algorithms, techniques, and strategies to bring users out of Filter Bubbles. These solutions aim to increase the diversity of recommendations and broaden users' horizons.

Overall, both streams of research are crucial in understanding and addressing the challenges posed by Filter Bubbles in Recommender Systems. Figure 5 presents the classification of the papers included in our research on filter bubbles. These papers are categorized into two primary areas: identification and mitigation of filter bubbles. Within each category, further subcategories are established based on the approaches adopted in the studies. This classification system allows for a systematic organization and analysis of the research conducted on filter bubbles, providing insights into the various methods and strategies utilized to tackle this issue.

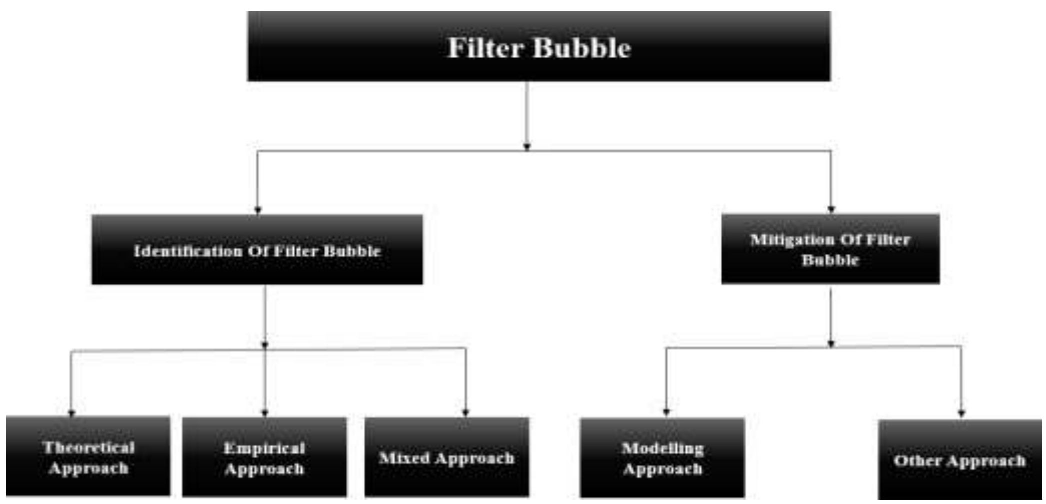

Fig 5: Classification of Filter bubble studies.

5.1. Identification of Filter Bubbles

The identification of filter bubbles in recommender systems involves three main approaches: theoretical analysis, empirical studies, and a combination of both theoretical and empirical methods. In this section, we will examine and categorize the studies that have utilized these approaches to shed light on the existence and impact of filter bubbles.

5.1.1. Theoretical Approach: Over time, researchers have utilized theoretical analysis to identify and comprehend the presence of filter bubbles within recommender systems. They have formulated conceptual frameworks and models to gain insights into the nature of filter bubbles in these systems. Additionally, mathematical modeling, simulations, and theoretical reasoning have been employed to examine the impact and consequences of filter bubbles in recommender systems. Through these approaches, researchers have advanced our understanding of the underlying dynamics and mechanisms associated with filter bubbles. (Bozdag and van den Hoven 2015) drew attention to the fact that various democratic ideologies place emphasis on various filter bubble characteristics. The study's findings show that the bulk of the methods used to counteract filter bubbles have been created with the standards of liberal or deliberative democratic models in mind.

(Chitra and Musco 2019) developed a mathematical framework based on the Friedkin-Johnsen model to investigate the filter bubble theory. Through theoretical analysis, they provided support for the identification of filter bubbles and proposed modifications to the existing model. The results of Nguyen et al. are explained using a numerical simulation technique proposed by (Aridor, Goncalves, and Sikdar 2020). This model the significance of compiling information about user attitudes and how they have changed over time. (Berman and Katona 2020) in their paper studied the role of curation algorithms in shaping users' exposure to content on social networks and their potential impact on the formation of filter bubbles. The study includes a theoretical model that incorporates content creators, content consumers, and a curating platform.

(Michiels et al. 2022) offers an operationalized definition of the technological filter bubble. They have expanded upon Pariser's initial argument as conceptualized by Dahlgren. To further the concept's accuracy and clarity, the authors sought to establish a completely experimental definition of the technical filter bubble. Moreover, (Keijzer and Mäs 2022) explored the contributions of personalization and polarization in communication systems. They emphasized the importance of taking a complex approach to foresee and avoid negative consequences of communication technologies on democratic decision-making and public discourse.

Collectively, these studies highlight the wide range of theoretical approaches used to analyze filter bubbles, including mathematical frameworks, simulations, and operational definitions. Table 2 provides a comprehensive summary of studies that have utilized theoretical methods to identify and examine filter bubbles in recommender systems.

Table 2: Brief Summary of theoretically used approaches to identify filter bubbles.

Paper Ref.	Title	Approach
(Bozdag and van den Hoven 2015)	*"Breaking the filter bubble: democracy and design"*	Study of various software architectures and techniques that aim to disrupt filter bubbles.
(Chitra and Musco 2019)	*"Understanding Filter Bubbles and Polarization in Social Networks"*	Developed a mathematical Framework to identify filter bubble in social networks.
(Aridor, Goncalves, and Sikdar 2020)	*"Deconstructing the Filter Bubble: User Decision-Making and Recommender Systems"*	A numerical simulation approach to provide explanations for Nguyen et al. work.
(Berman and Katona 2020)	*"Curation Algorithms and Filter Bubbles in Social Networks"*	Developed a theoretical model which analyzed the impact of curation algorithms in social networks.
(Michiels et al. 2022)	*"What Are Filter Bubbles Really? A Review of the Conceptual and Empirical Work."*	A review of all the empirical work done for filter bubbles in recommender systems. Provides an operationalized definition for filter bubble
(Keijzer and Mäs 2022)	*"The complex link between filter bubbles and opinion polarization."*	Complexity approach to anticipate and prevent filter bubbles and personalization.

5.1.2. Empirical Approaches: In contrast to theoretical studies, empirical research on filter bubbles in recommender systems takes a practical approach by utilizing real-world data and conducting experiments. These studies involve the collection of user data, analysis of user behavior, and measurement of the degree of personalization and biases present in recommendations. Empirical investigations employ various approaches such as case studies, probabilistic analysis, quantitative assessment, and analytical methods. By adopting empirical methodologies, researchers gain valuable insights into the actual impact and manifestations of filter bubbles in recommender systems, providing a more realistic and data-driven understanding of the phenomenon. In recent years, a significant portion of research on filter bubbles in recommender systems has relied on empirical approaches for identification and analysis. In this section, we will provide a concise overview of some notable studies in this field.

(Nguyen et al. 2014) conducted a study to investigate the longitudinal effect of a collaborative filtering-based recommender system on users. To conduct this study, they used a real world movie dataset called Movie Lens. (Nikolov et al. 2015) used a sizable dataset of online visits to mine social bias at the collective level and quantify it. According to this study's data, users use social media to get information from a substantially smaller range of sources than they would using traditional search engines. Hence, this indicates that recommendation algorithms used in social media streams contribute to the generation of filter bubbles. In a study, *Information Segregation* measure was introduced to capture the notion of exposure to different information by different population in a society (Chakraborty, Abhijnan, et al., 2017). Hence this research proposed a method / measure to quantify filter bubble or echo chamber effect.

A case study was done by (Courtois, Slechten, and Coenen 2018) which did not support the evidence of Filter bubbles in social media. They focused on Google search results for a set of socio-political queries. The results indicated that mainstream media dominated the search results, followed by civil society and government resources. Hence, this study did not support the filter bubble hypothesis. (Nechushtai and Lewis 2019) investigated the impact of news recommendations on the formation of filter bubbles and the fragmentation of news audiences. They conducted an empirical study using Google News and recruited 168 participants who had different political beliefs and were from various states. The participants were asked to use their Google accounts to search for news about the 2016 US presidential campaign candidates. The first five recommended news stories were recorded. The study found that the news recommendations were very similar among users with different political beliefs and from different states, indicating the presence of filter bubbles.

A novel metric to gauge the influence of filter bubbles by analysing the homogeneity of item lists was introduced by (Lunardi et al. 2020). The study utilized a dataset of news of 2018 Brazilian presidential elections. The study also explored whether diversification techniques can help reduce filter bubble effect in recommender systems. When it comes to YouTube's recommendation system very less is known, thus there is not a lot of experimental research on filter bubble in YouTube. The study conducted by (Kim et al. 2021) conducted an indirect study to demonstrate the existence of filter bubbles on YouTube. They achieved this by extracting a comment-based content network between uploaders and users who commented on the videos, and analysed the communication patterns between users using Social Network Analysis (SNA). The analysis revealed that users were experiencing narrow information acquisition and communication, which was attributed to the presence of filter bubbles on YouTube.

(Huellmann, Sensmeier, and Sensmeier 2022) conducted an online study to investigate the impact of personalization on news diversity. They used two types of profiles, personalized and non-personalized, and queued news articles from two news aggregators, namely Google News and Flipboard. Interestingly, they found that personalization of Google News increased news diversity, while personalization of Flipboard decreased it. Furthermore, when they compared the absolute values for news diversity, they found no significant differences between personalized news aggregators and edited news websites, indicating no filter bubble effect for the variety of themes in news. Hence this study did not support the filter bubble hypothesis. In another research a framework to evaluate the effect of filter bubbles on news recommendations is developed by (Han et al. 2022). This framework consists of four phases - Selection, Setup, Link, and Evaluation, which aims to exploit the filter bubble effect of personalized news aggregation and recommender systems. They applied this framework to study three Chinese news aggregators, Toutio, Baidu News, and Tencent News, to demonstrate the effectiveness of their approach. The study found that filter bubble is being formulated hence narrowing the range of topics which are presented to the users.

Therefore, several noteworthy empirical studies have been conducted to examine the presence of filter bubbles in recommender systems. While a majority of these studies support the filter bubble hypothesis, there are also somestudies that do not provide evidence in favour of filter bubbles. Table 3 presents a comprehensive list of these empirical studies, along with the findings regarding the detection of filter bubbles in recommender systems.

Table 3: Brief Summary of empirically used approaches to identify filter bubbles.

Paper Ref.	Title	Approach	Data Used	Filter Bubble Identified?
(Nguyen et al. 2014)	*“Exploring the Filter Bubble: The Effect of Using Recommender Systems on Content Diversity”*	Investigated the longitunal effect of a Collaborative filtering Algorithm. Examined diversity of recommendations at individual level	Movie Lens Dataset	YES
(Tran and Herder 2015)	*“Detecting Filter Bubbles in Ongoing News Stories”*	They used a random walk model to rank dates. After that, they re-ranked the top selected dates basedon Shannon Diversity Index(SDI) scores.	Crisis data	YES
(Nikolov et al. 2015)	*“Measuring Online Filter Bubbles”*	Measured social Bias Quantitavely. They Imposed content diversity on different online media	Click Dataset	YES
(Dillahunt, Brooks, and Gulati 2015)	*“Detecting and visualizing filter bubbles in Googleand Bing”*	Utilized Search Engines like Google and Bing to explore for Filter Bubbles. Used a combination of human analysis and automated methods	Data from Google and Bing	YES
(Abisheva, Garcia, and Schweitzer 2016)	*“When the Filter Bubble Bursts: Collective Evaluation Dynamics in OnlineCommunities”*	examined the collective evaluation process of online content through positive and negative votes in various social media platforms	YouTube, Reddit, Imgur, andUrban Dictionary	YES
(Chakraborty, Abhijnan, et al., 2017)	*“On Quantifying Knowledge Segregation in Society”*	Used Information Segregation measures to measure Filter Bubbles. Capture the concept of information diversity among users in society.	Data from Facebook by searching the term ‘US news Media’	YES
(Haim, Graefe, and Brosius 2018)	*“BURST OF THE FILTER BUBBLE? Effects of personalization onthe diversity of Google News”*	two empirical experiments were conducted to examinethe impact of implicit and explicit personalisation on the variety of material and sources in Google News.	Google NewsData	NO

(Courtois, Slechten, and Coenen 2018)	*"Challenging Google Search filter bubbles in social and politicalinformation: Disconforming evidence from a digital methods case study"*	Examined the Google search results using mixed model regression analysis. Tested weather Test results varied across different users	Search queryfrom Googlesearch was recorded for a representative 350 users who speak Dutch.	NO
(Mikki et al. 2018)	*"Filter bubbles in interdisciplinary research: a case study on climate and society"*	Searched for a defined set of keywords and analysedthe retrieved documents using various bibliometrictools such as Publish or Perish. assessed open availability, citations received, co- authors, and publication type	Data from Web Of Science (WoS) andGoogle Scholar.	YES
(Nechushtai and Lewis 2019)	*"What Kind of News GatekeepersDo We Want Machines to Be? Filter Bubbles, Fragmentation, andthe Normative Dimensions of Algorithmic Recommendations"*	Conducted an empirical study utilizing Google News, enlisting 168 participants with diversepolitical beliefs from various states.	Data from Google News Users.	YES
(Lunardi et al. 2020)	*"A metric for Filter Bubble measurement in recommender algorithms considering the news domain."*	Created a prototype that suggests news items and displays those suggestionson a feed. Introduced a novel metric to measure the filter bubble	News data from 2018 Brazilian presidential elections	YES
(Liu et al. 2021)	*"The Interaction between Political Typology and Filter Bubbles in News Recommendation Algorithms"*	Investigated how various algorithmic tactics impact filter bubble development through simulated studies. Identified heterogeneous effects based on the user'spre-existing preferences.	Collected over 900K news articlesfrom 41 different sources	YES
(Vancompernolle Vromman and Fouss 2021)	*"Filter bubbles created by collaborative filtering algorithmsthemselves, fact or fiction? An experimental comparison"*	Tested various collaborative filtering algorithms and their impacton the diversity and noveltyof recommended items. Examined different user behaviour configurations to assess the effect of user preferences on diversity and novelty.	Movie Lens 100K	YES

(Kim et al. 2021)	*"An Empirical Study on Filter Bubbles in the YouTube CommentsNetwork: Using Social Network Analysis"*	Extracted a comment-based content network between uploaders and users who commented on the YouTube videos. Analyzed communication patterns between users through social network analysis (SNA).	Used NetMiner to collect YouTube Comment data	YES
(Huellmann, Sensmeier, and Sensmeier 2022)	*"No Filter Bubbles? Evidence From an Online Experiment on the News Diversity of Personalizing News Aggregators"*	Investigated the impact of personalization on news diversity. Used a fixed-effects model to measure the change in News Diversity.	Data from Google News and Flipboard	NO
(Han et al. 2022)	*"SSLE: A framework for evaluating* *the "Filter Bubble" 16ffect on the news aggregator and recommender"*	Proposed a framework consisting of four phases – Selection, Setup, Link, and Evaluation.	News datasetfrom Toutio,Baidu News,and Tencent News	YES

5.1.3. Mixed Approach: This type of approach has been employed by researchers to identify filter bubbles in recommender systems, combining both theoretical analysis and empirical data. In these studies, empirical data is used to complement and validate the theoretical frameworks or analyses developed by the researchers. The integration of theoretical and empirical approaches provides a more comprehensive understanding of filter bubbles. Overall, the combination of theoretical and empirical analysis provides a more holistic and nuanced perspective on filter bubbles in recommender systems, facilitating the development of effective strategies and countermeasures to mitigate their negative impact. In the following section, we will explore some relevant literature that has successfully employed these mixed approaches to identify and examine filter bubbles in recommender systems.

(Yao, Hauptmann, and Post 2018) leveraged the collective wisdom of the crowd to address the reviewer selection problem, specifically targeting the identification of reliable reviews for potential rumors. They conducted a comprehensive theoretical study, providing insights into the underlying principles of reviewer selection. Additionally, they devised a greedy algorithm with an approximation guarantee, offering a practical solution to the problem. To validate the effectiveness of their theoretical analysis and algorithm, the researchers performed experiments on a dataset sourced from Twitter, focusing on the context of rumors. In their study,(Massand and Nath 2018) addressed the concept of surprise in elections and put forth a mathematical model that incorporated both global and local information. The researchers utilized real-world data from the UK-EU referendum, popularly known as BREXIT, to substantiate their theoretical predictions.

(Smets, Montero, and Ballon 2019) argue that algorithmic impact assessments should encompass the urban context to prevent the emergence of urban filter bubbles. To substantiate this claim, the researchers conducted a survey among urban residents in Brussels, Belgium. The findings of the study revealed that individuals residing in more diverse neighborhoods were more likely to encounter a variety of viewpoints in their media consumption. However, the research also highlighted that personalized media content played a role in the formation of filter bubbles.

Hence, these studies represent examples where a combination of theoretical and empirical approaches has been employed to investigate and identify filter bubbles in recommender systems. A comprehensive list of such studiescan be found in Table 4.

Table 4: Brief Summary of mixed approaches used to identify filter bubbles.

Paper Ref.	Title	Approach	Data
(Yao, Hauptmann, andPost 2018)	*"News Recommendationand Filter Bubble"*	Addressed the issue ofreviewer selection for identifying trustworthy reviews related to potential rumors. Offered practical solution to this theoretical approach.	Twitter data focusing on context of rumors
(Massand and Nath 2018)	*"Quantifying Filter Bubbles: Analyzing Surprise in Elections"*	Proposed a Mathematicalmodel to address surprisein Elections.	Real World Data fromUK-EU Referendum, commonly known as BREXIT.
(Smets, Montero, andBallon 2019)	*"Does the Bubble Go Beyond? An Explorationof the Urban Filter Bubble."*	Advocate for urban context in algorithmic impact assessments to prevent filter bubbles by conducting a user survey.	Data collected from thesurvey done among urban residents in Brussels, Belgium.

5.2. Mitigation of Filter Bubbles

Researchers have employed various strategies to address the challenge of filter bubbles in recommender systems.These approaches can be categorized into two main types: modelling approach and other approach. The modelling approach involves the development of new prototypes or models specifically designed to mitigate the filter bubble issue. On the other hand, the other approach encompasses modifications to existing recommender system algorithms, as well as theoretical and empirical methods proposed to tackle the problem. By adopting these diverse approaches, researchers aim to combat filter bubbles and enhance the effectiveness and diversity of recommendations in recommender systems. This section will delve deeper into the various approaches utilized toaddress the filter bubble issue in recommender systems. We will explore these approaches in detail to gain a comprehensive understanding of how researchers are working to solve the problem of filter bubbles in recommender systems.

5.2.1. Modelling Approach: Over the years, researchers have dedicated their efforts to developing innovative modelsand frameworks as part of the modelling approach to address the challenge of filter bubbles within recommender systems. In this section, we will explore several noteworthy studies that have made significant contributions to addressing these problems.

(Pardos and Jiang 2019) proposed a modification to the skip-gram model, which was used to handle nine years ofcourse enrolment data. They named this model multifactor2vec. The offline testing of the model showed improved accuracy and recall on their course similarity and analogy validation sets compared to a standard skip-gram. Additionally, in order to counteract the filter bubble, (Symeonidis, Coba, and Zanker 2019) presented a frameworkto tackle the filter bubble problem by proposing two models based on novel matrix factorization (NMF). The twomodels are popularity-based and distance-based NMF. The experimental results show that the models attain highaccuracy by recommending also novel items.

The Personalized Unexpected Recommender System (PURS) model proposed by (Li et al. 2020) to address filterbubbles by incorporating unexpectedness in recommendations. The model outperformed baseline approaches in accuracy and unexpectedness measures through rigorous offline testing on Yelp, Movie Lens, and Youku datasets. Online A/B testing on Alibaba-youku also yielded positive results, leading to its potential deployment by the company.(Amrollahi 2021) introduced an integrated tool to combat filter bubbles in social networks. By analyzingresearch papers, the author classified content and integrated an agent mechanism that monitors content diversity and triggers a filter bubble alarm.

User Controllable Recommender System (UCRS), a novel recommender prototype proposed in another work, allowing users to actively regulate the mitigation of filter bubbles (W. Wang et al. 2022). They created a system called User-Controllable Inference (UCI) that can swiftly modify suggestions in response to user controls. The approach was evaluated on three datasets, demonstrating high accuracy and diversity in recommending desired items based on user controls. (Sun et al. 2022) proposed a cross-domain matrix factorization model with adaptive diversity regularization to combat the filter bubble problem. The researchers evaluated their proposed model usingthe Douban dataset, with Movies as the target domain and Books as the source domain. The model achieved a balance between accuracy and diversity of recommendations and helped reduce polarization of viewpoints amongusers.

Hence, these studies represent notable contributions in using the modelling approach to address the issue of filter bubbles in recommender systems. A comprehensive list of these studies, including the approaches, datasets used,and results, is provided in Table 5.

Table 5: Summary of Modelling approaches incorporated to mitigate filter bubbles.

Paper Ref.	Title	Approach	Dataset Used	Results
(Pardos and Jiang 2019)	*"Combating the Filter Bubble: Designing for Serendipity in a University Course Recommendation System"*	Novel alterations to the conventional skip-gram model. Model is called MultiFactor2Vec	dataset with anonymized enrollment data for UC Berkeley courses from Fall 2008 through Fall 2017.	Offline testing showed better Recall and Accuracy on the course similarity. The multifactor2vec model boosted novelty and offeredserendipitous suggestions to counter filter bubbles.
(Grossetti, duMouza, and Travers 2019)	*"Community-Based Recommendations on Twitter: Avoiding the Filter Bubble"*	a rigorous analysis of a large Twitter dataset, was done to testfor filter bubble. proposed the Community AwareModel (CAM), which uses community similarities to re- rank recommendation lists and mitigate filter bubble effect	Twitter Dataset	Results showed thatfilter bubble hampered around 10% of the users. It also boosted theaccuracy of recommendationsby 14%
(Symeonidis, Coba, and Zanker 2019)	*"Counteracting the filter bubble in recommender systems: Novelty- aware matrix factorization"*	Two models based on novel matrix factorization (NMF) were proposed. One being popularity-based NMF and another distance-based NMF,which extend the simple itemnovelty model.	Movie Lens 100K, Movie Lens 20M, Yelpand Movie Lens1ML.	The proposed approach showed a balanced trade-off between Novelty and Precision. The method also provides more novel items when compared to other algorithms

(Li et al. 2020)	*"PURS: Personalized Unexpected Recommender System for Improving User Satisfaction"*	A brand-new "Personalized Unexpected Recommender System" (PURS) is suggested. Unexpectedness is incorporatedinto the recommendation process in this paradigm.	Yelp, Movie Lens, and Youku	Model outperformed baseline approaches in accuracy and unexpectedness measures through rigorous offline testing. Online A/B testing on Alibaba-youku also yielded positive results.
(Amrollahi 2021)	*"A Conceptual Tool to Eliminate Filter Bubbles in Social Networks"*	An Integrated Tool to help avoid Filter Bubbles in social networks. Classification of research studies is done to develop the overall architecture of the tool	Data from six scientific databases was used to select the papers through whichthe tool was developed.	the tool recommended users with new and diverse content to break the filter bubble.
(Portenoy et al. 2022)	*"Bursting Scientific Filter Bubbles: Boosting Innovationvia Novel Author Discovery"*	Proposed a new framework called 'Bridger'. This approach locates commonalities and contrasts between scientists to balance relevance and novelty.	Data from Microsoft Academic Graph (MAG)	The faceted approach was effective in identifying authorswhose work is considered more innovative and interesting. Bridger framework identifies authors from diverse sources (venues, citations, co-authorship) indicating its abilityto discover authors from distant communities.
(C. Gao et al. 2022)	*"CIRS: Bursting Filter Bubbles by Counterfactual Interactive Recommender System"*	A new counterfactual interactiverecommender system (CIRS) developed. Utilizes a causal user model thatis learned from historical data toidentify item overexposure to RL policy planning..	VirtualTaoba oand KuaiEnv	the proposed modelcan increase users' overall satisfaction and mitigate the filter bubble issue. Balances high satisfaction per round with lasting interaction.
(Z. Gao et al. 2022)	*"Mitigating the Filter Bubble while Maintaining Relevance: Targeted Diversification with VAE-based Recommender Systems"*	Introduces Concept Activation Vectors (CAVs) for targeted topical dimensions like political polarization. State-of-the-art VAE-based recommender system that diversifies latent embeddings along targeted dimensions while maintaining topical relevance across orthogonal dimensions.	Reddit and Yelp	The approach betterpreserves the relevance of contentto user preferences across a range of diversification levels. The proposed method is computationally more efficient thanthe previous post- hoc re-ranking approach of MMR. .

(W. Wang et al. 2022)	*"User-controllable Recommendation Against Filter Bubbles"*	Suggested the User ControllableRecommender System (UCRS) as a new recommender prototype to manage filter bubbles. Created a framework for user-controllable inference (UCI) that can swiftly modify suggestions in response to usercontrols.	DIGIX-Video, Movie Lens 1M (ML1M) and Amazon Book	Studies demonstratethat the UCI framework can successfully suggest more preferred items depending on user settings. Addresses the accuracy-diversity conundrum by reducing group segregation in filter bubbles while preserving high accuracy and boosting diversity relative to FM and NFM.
(Sun et al. 2022)	*"Prick the filter bubble: A novel cross domain recommendation model with adaptive diversity regularization"*	To address the filter bubble issue, a cross-domain matrix factorization approach with adaptive diversity regularizationwas put forth. Approach uses social tagging, adaptive diversity regularization, and collective matrix factorization for improved recommendation performance.	Douban Dataset:with Movies as Target Domain and Books as Source Domain	Experiments confirm social tags' effectiveness in addressing sparsityin the target domain. The model achieveda balance between accuracy and diversity of recommendations.

5.2.2. Non-Modelling Approach: In addition to the modelling approach, researchers have also explored non- modelling approaches to address the filter bubble problem in recommender systems. These approaches involve algorithmic modifications and other strategies aimed at mitigating the issue. In the following section, we will examine several notable studies that have employed these approaches to tackle the problem of filter bubbles.

(Nagulendra and Vassileva 2014) developed an interactive visualization tool that allows social media users to be aware of and control personalized filtering mechanisms. They carried out research with 163 participants and found that visualization raised users' awareness of filter bubbles and provided transparency and control over their content consumption. (Reviglio 2017) proposes serendipity as a possible solution to counteract the negative effects of filter bubbles. He suggests that this approach has the potential to assist in designing systems that promote serendipity and increase users' exposure to diverse ideas and perspectives.

The filter bubble problem is examined from the standpoint of algorithm fairness in a research by (Masrour et al. 2020), who also present a dyadic-level fairness criteria based on network modularity measure. They proposed twoapproaches to address this issue: a greedy postprocessing method based on Modred measure and an adversarial learning framework. Experimental results on real-world datasets showed that these methods effectively reduced the modularity of predicted networks while maintaining prediction accuracy. (Srba et al. 2023) examined the formation of misinformation filter bubbles and potential mitigation strategies. Using pre-programmed agents, they accessed misinformation-promoting content and attempted to burst the bubble by watching debunking content. The study revealed that while filter bubbles may not always emerge, they can be disrupted by engaging with debunking content.

Filter bubbles are shown by (Hirschmeier 2022) as dynamic, slowly changing constructions that support temporal dynamics and are continually changed by both machine and human activity. The author proposed a method to address filter bubbles in digital journalism by considering their temporal dynamics. They developed and tested a personalized radio application on smartphones to evaluate its effectiveness. The results demonstrated that adjusting filter bubbles can enhance the co-creation of information flows between listeners and broadcasters.

Therefore, these are a few significant studies that have employed non-modelling approaches to address the issue of filter bubbles. Table 6 provides a comprehensive list of all the research conducted to mitigate filter bubbles inrecommender systems.

Table 6: Summary of Non-Modelling approaches incorporated to mitigate filter bubbles.

Author and Year	Title	Approach	Dataset Used	Results
(Nagulendra andVassileva 2014)	*"Understanding and Controlling the Filter Bubble through Interactive Visualization: A User Study"*	An Interactive Visualization is proposed which enables users to be aware of personalization mechanism. It is used in a peer-to-peer socialnetworking system.	Data from 163 participants is recorded to conduct a quantitative study.	Users' understanding of the filtering process and awareness of the filter bubble were both influenced by the visualization.
(Foth et al. 2016)	*"Citizens Breaking Out Of Filter Bubbles: Urban Screens as Civic Media"*	Discussed the potential of UrbanInterfaces to promote social and cultural Diversity. The creation of a theoretical framework positioning ubiquitous screens and other urban interfaces as civil mediahas been suggested.	Since a theoretical approach and solution so no real world data.	Empirical analysis suggests urban screens can counteract negative aspects of social media by breaking users out of filter bubbles, if designed beyond advertising or TV broadcasts.
(Reviglio 2017)	*"Serendipity by Design? How to Turn from Diversity Exposure to Diversity Experience to Face Filter Bubbles in Social Media"*	Proposed Serendipity as a possible solution to evaluate filter bubbles. A theoretical analysis.	A Theoretical approach so no dataset was used.	Highlights potentialfor this approach todesign systems promoting serendipity and diverse exposure..
(Ookalkar, Reddy, and Gilbert 2019)	*"Pop: Bursting NewsFilter Bubbles on Twitter Through Diverse Exposure"*	Proposed a Google Chrome Extension called "POP". Consolidates diverse tweets fromnews sources, bursting filter bubbles and promoting diverse exposure in users' Twitter feeds.	Twitter data	By displaying tweets from many news outlets about the same news occurrence, the method promotes diversified exposure.
(Masrour et al. 2020)	*"Bursting the Filter Bubble: Fairness-Aware Network Link Prediction"*	Approach focuses on dyadic-level fairness criterion using network modularity measure. Used this criterion as a post-processing step to generate diverse recommendations. Proposed a unique method that addresses filter bubbles by combining supervised link prediction with adversarial network representation learning.	Dutch School, Facebook and Google+.	Proposed methodsreduce modularityof the predicted network.

(Hirschmeier2022)	*“Managing TemporalDynamics of Filter Bubble”*	Create a strategy for dealing withfilter bubbles in online journalism by conceiving and creating the temporal dynamics of these bubbles. This was accomplished by enabling users to interact with filter bubbles through ongoingco-creation to match their ownpicture with that of others.	A smartphone app for customized radio was created, evaluated, and data was gathered.	Based on the findings, filter bubble settings canimprove the co- creation of information flows between listeners and broadcasters. The study offers atheoretical framework for the early control of filter bubbles.
(Anand, Yang,and Zhao 2022)	*“Mitigating Filter Bubbles within Deep Recommender Systems”*	Developed a method to classify data points and mitigate filter bubbles based on user-item interactions. Employed TracIN method to determine influences between categories. Also developed a simple LSTM recommender system.	Twitch Dataset	Significant improvements in diversity metric. It mitigated the filterbubble without compromising accuracy significantly
(Srba et al. 2023)	*“Auditing YouTube’s Recommendation Algorithm for Misinformation Filter Bubbles.”*	examined the formation of misinformation filter bubbles. Discuss potential filter bubble mitigation strategies. using a "sock puppet audit methodology," in which pre-programmed agents enter "filter bubbles of misinformation." Discussed that by seeing debunking media filter bubbles can be burst.	Data from 17405unique YouTubeVideos.	In comparison to other research of a comparable nature, there was no appreciable improvement in the overall quantity of acceptable misleading material.

The aforementioned were papers that presented approaches and frameworks aimed at addressing the filter bubbleproblem in recommender systems.

5.3. Notable Solutions

Over the years, researchers have proposed various approaches to address the problem of filter bubbles in recommender systems. These approaches include the development of frameworks as well as different strategies to tackle this issue. A detailed review of these approaches is presented in section 4.2. In this section, we will highlight some of the commonly used and noteworthy approaches that researchers have used to mitigate the impactof filter bubbles in recommender systems.

Various frameworks have been proposed by researchers to mitigate filter bubbles in recommender systems, withthe aim of incorporating user feedback into the recommendation process and giving users control over their recommendations. (W. Wang et al. 2022) proposed the User Controllable Recommender System (UCRS), which alerts users of filter bubbles, supports different levels of control commands, and adjusts recommendations based on user feedback. The incorporation of user controls in recommender systems can help externally specify users' interests, leading to better recommendations. In the future, different frameworks that incorporate user controls canbe developed to reduce filter bubbles in recommender systems.

A strategy is to add surprise in suggestions to combat filter bubbles in recommender systems. (Li et al. 2020) proposed a PURS, or a Personalized Unexpected Recommender System, which includes surprise and unpredictability into the recommendation process. Results showed that PURS performed significantly well on thevideo platform Alibaba-Youku, and it is currently being deployed by the platform. Further research can be conducted to improve this approach in the future.

Along with frameworks, diversity-based approaches are commonly used to alleviate filter bubbles in recommender systems. While diversity-based approaches may not always provide the most relevant recommendations, they can be utilized to mitigate filter bubbles. (Sun et al. 2022) developed a cross-domain matrix factorization model that incorporates adaptive diversity to control filter bubbles. This model achieved a decent balance between accuracy and diversity. By incorporating deep learning techniques, this approach can befurther improved to reduce filter bubbles in recommender systems.

In order to mitigate filter bubbles in recommender systems, another approach that is commonly used is the fairness-oriented recommender system. One objective proposed by (Steck 2018) is the calibration, which ensures that the proportion of item categories in the recommendation list follows the user's historical interactions. Fairnesscan be a useful factor in developing a recommender system model to mitigate filter bubbles.

Researchers have proposed different methods to address the issue of filter bubbles in recommender systems. These methods can be classified into two categories, namely pre-processing and post-processing techniques. Pre- processing techniques involve the manipulation of user-item interaction data before the recommendation process, while post-processing techniques manipulate the recommendations after the recommendation process. Pre- processing techniques aim to reduce the effect of filter bubbles by manipulating the data. Post-processing techniques aim to reduce the effect of filter bubbles by re-ranking or diversifying the recommendations. For example, (Z. Gao et al. 2022) diversified the recommendations in a VAE-based recommender system by modulating the latent embeddings to ensure topical relevance across orthogonal dimensions. Therefore, developing a model that employs these techniques can help in mitigating the issue of filter bubbles in recommender systems. Moreover, ethical considerations such as transparency, accountability, and privacy should be taken into account while designing recommender systems to ensure fairness and avoid unintended biases.

In a study conducted by (S. Wang et al. 2014), a novel multi-objective evolutionary algorithm was proposed to optimize two objective functions that often contradict each other: accuracy and novelty. This approach was initially intended for long tail recommendations, which recommend less popular items to users. The study uses multi objective optimization-based recommender systems. Although the approach did not directly focuses on filter bubbles, it focused on long tail problem of recommender systems which can lead to filter bubble.

In Table 7, we have critically analyzed the state of art approaches. In summary, various techniques and solutions have been proposed by researchers to mitigate filter bubbles in recommender systems. The approaches discussed above include frameworks, surprise-based recommendations, diversity-based recommendations, and fairness- oriented recommender systems. These approaches have shown promising results in reducing the filter bubble effect and providing more diverse and relevant recommendations to users.

Table 7: Critical Analysis of Approaches used for filter bubble handling.

Approach	Advantages	Limitations
Unexpectedness in Recommendations	Introducing surprise/ unexpectedness in recommendations offers users novel and unexplored suggestions. Exploration of Items is increased as wellas enhance in serendipity.	• There is a risk of irrelevance i.e., recommendingunexpected items can cause users to lose interest. • Introducing unexpectedness may require diverting from personalized recommendations resulting in Accuracy and Diversity Tradeoff.
User-Controllable Recommendations	The incorporation of user controls in recommender systems can help externally specify users' interests, leading to better recommendations. Also, user controllable recommendationscan lead to a personalized experience as an individual can tailor the recommendations according to his/her taste.	• If users are unaware of the filter bubble theory,it can be tough for them to mitigate filter bubbles. • User-controlled recommendations may prioritize user-defined preferences to the extent that serendipitous discoveries are minimized.
Fairness based Recommender Systems	Promotes diversity and reduces bias inthe recommendations	• Trade-offs between accuracy and fairness, leading to a suboptimal user experience. • Incorporating fairness considerations into recommender systems introduces additional complexity and computational overhead
Multi Objective Optimization based Recommender systems	The ability to balance multiple objectivessimultaneously, such as personalization and diversity can lead to better recommendations and can help mitigate filter bubbles.	• Multi-objective optimization may not fully capture individual user preferences and satisfaction, hence can lead to user dissatisfaction. • Complex objectives, trade-offs, and computational demands in recommender systems.
Diversity Based Recommender Systems	Enhances exposure to diversified contentand perspective. Discovers new recommendations which wouldn't have been possible by using traditional recommender systems.	3. Increased diversity comes at the expense of personalized recommendations hence there is a tradeoff with accuracy/ personalization. 4. A diverse set of recommendations may overwhelm users with excessive options leadingto information overload.

6. OPEN CHALLENGES

The filter bubble problem brings forth a set of persistent challenges that require thorough examination and resolution. These challenges, as depicted in Figure 6, encompass various aspects related to the filter bubble problem. In this section, we have provided an in-depth analysis and discussion of each of these challenges. By identifying and addressing these challenges, we can strive towards mitigating the adverse effects of the filter bubble phenomenon and fostering a more diverse and inclusive information ecosystem.

Fig 6: Open Challenges of Filter bubble Problem

One key challenge is the domain specificity of the issue, as filter bubbles manifest differently across diverse domains. In the realm of news, addressing the filter bubble becomes particularly arduous. Users often find themselves exposed solely to news and information that align with their existing perspectives, resulting in a limited exposure to diverse viewpoints. This phenomenon can aggravate concerns such as the dissemination of fake news and the reinforcement of polarized opinions within societies. Similarly, within the domain of movies and entertainment, the filter bubble poses a distinct challenge. Individuals are frequently recommended similar items based on their preferences, which, over time, can lead to a lack of variety and monotony. Consequently, the filter bubble in this domain presents its own set of disadvantages. Conversely, in e-commerce recommendations, the filter bubble may not pose a threat as individuals typically desire receiving similar recommendations. Consequently, domain specificity stands as a significant open challenge in addressing the filter bubble problem. Overcoming this challenge necessitates tailored strategies and solutions that acknowledge the unique dynamics and requirements of each domain. By comprehending and addressing these domain-specific challenges, researchers and practitioners can devise effective approaches to mitigate the filter bubble problem and promote diversity and user satisfaction across different domains. While it is likely that this problem will persist, efforts canbe made to minimize its impact and mitigate filter bubbles in recommender systems.

Another significant open challenge in relation to the filter bubble problem pertains to its ethical implications. It is imperative to uphold ethical practices in the context of content curation and recommendation algorithms. This entails addressing various concerns, including algorithmic bias, discrimination, and the unintended consequences that may arise from personalized content delivery. Furthermore, it is essential to take into account user privacy and data protection considerations. Striking a balance between providing personalized recommendations and respecting user autonomy and privacy is a complex task. Ethical considerations must be integrated into the design and implementation of recommendation systems to mitigate the potential negative effects of filter bubbles and ensure fair, transparent, and responsible practices. By promoting ethical guidelines and standards, researchers and practitioners can work towards fostering trust, inclusivity, and accountability in the development and deploymentof recommendation algorithms.

The challenge of striking a balance between personalization and diversity remains a significant and persistent issue in addressing the filter bubble problem. On one hand, personalized content recommendations tailored to individual preferences offer valuable benefits, enhancing user satisfaction and engagement. However, solely relying on personalization can inadvertently contribute to the formation of filter bubbles, limiting users' exposureto diverse perspectives and information. On the other hand, an excessive focus on diversity can result in subpar and inaccurate recommendations, potentially leading users to disregard the recommendations altogether. Therefore, finding the right balance between personalization and diversification is crucial to mitigate the filter bubble problem effectively. Nonetheless, achieving this balance is not a simple task, as personalization and diversification often represent opposing forces. Despite the inherent challenges, researchers and practitioners strive to optimize the trade-off between personalization and diversity, aiming to provide users with relevant and varied content while mitigating the risks of information homogeneity and limited exposure. Although this dilemma may not have a definitive resolution, ongoing efforts are focused on addressing this challenge to the bestextent possible.

Addressing the filter bubble problem involves grappling with additional challenges, such as finding the right balance between user control and algorithmic recommendations. While personalized content based on user preferences can enhance the user experience, it is equally important to provide users with transparency and control over these recommendations. This brings forth the challenge of algorithmic transparency, as many recommender platforms lack transparency regarding their algorithms. Without visibility into how recommendations are generated, there is a risk of exacerbating the filter bubble problem. When users are trapped within a filter bubble,they have limited access to information sources outside their usual networks or platforms they heavily rely on. Bridging the digital divide and ensuring equitable access to information and diverse viewpoints thus becomes a critical challenge in combating the filter bubble problem. Efforts must be made to empower users with control over their recommendations while promoting algorithmic transparency to mitigate the adverse effects of information homogeneity and limited exposure to diverse perspectives.

7. FUTURE WORKS AND POSSIBLE SOLUTIONS

While research on the topic of filter bubbles in recommender systems is still in its early stages, this review has highlighted some possible solutions proposed by researchers to mitigate the problem. However, there is still muchto be done in this field, and several future works have been suggested to further alleviate filter bubbles in recommender systems. These future works include developing models that take into account user diversity, incorporating context and user intent into the recommendation process, developing more transparent and interpretable recommender systems, and considering ethical implications such as privacy concerns and fairness. By addressing these areas, it may be possible to create more effective and equitable recommender systems that better serve users. Here, we have presented some potential strategies that can assist in mitigating filter bubbles inthe future.

7.1. Explainable Recommender Systems

One way to address filter bubbles in recommender systems is to involve users in the recommendation process byenabling them to control the degree of personalization and informing them about the presence of filter bubbles. This can be achieved by incorporating Explainable AI (XAI) in the system. XAI refers to a set of methods and techniques that allow users to comprehend and trust the outputs and results generated by an AI model. The primary objective of an XAI system is to make the behavior of AI models more transparent and comprehensible to humans by providing explanations. In order to achieve this, an XAI system should be able to explain its capabilities, understandings, and actions to users, as well as provide clear explanations of how it produces its desired outputs.

It is possible to apply the methodology of XAI to recommender systems, resulting in the development of Explainable Recommender Systems. It provides users with complete explanations about how recommendations are generated and why they are generated. Such explanations are crucial to build trust and ensure that users are not trapped in filter bubbles. For instance, (Yera, Alzahrani, and Martínez 2022) explores the use of explanationsfor a nutrients/recipes recommendation system. This system not only explains why a recommendation is enjoyable but also evaluates the healthiness of the recommendation. The authors use a post-hoc explainability approach and apply it to multiple recipe recommendations. Such explainable recommender systems can help find a balance between accuracy and other metrics and prevent users from being trapped in filter bubbles.

One way to mitigate the filter bubble problem is to incorporate users in the recommendation process by allowing them to control the degree of personalization and by alerting them about the potential consequences of filter bubbles. In the future, we can utilize Explainable Recommender Systems, such as the one used in the nutrient/recipes recommendation system, to address the filter bubble issue. By providing explanations, we can strike a balance between accuracy and other metrics, thus preventing users from being confined within a bubble.

7.2. Utilizing Generative AI for Filter Bubble Mitigation in Recommender Systems:Tracking, Alerting, and Generating Fresh Recommendations

To address the issue of filter bubbles in recommender systems, the integration of Generative AI can be a valuableapproach. By actively tracking filter bubbles and providing users with alerts when they are trapped within one, the system can promote awareness and encourage users to seek diverse recommendations.

One key advantage of utilizing Generative AI is its ability to generate fresh and personalized recommendations. By leveraging advanced machine learning algorithms, Generative AI models can generate recommendations thatbreak free from the limitations imposed by filter bubbles.

The integration of Generative AI in recommender systems enables proactive measures to mitigate filter bubbles, empowering users with control over their content consumption. By combining tracking, alerting, and generating mechanisms, recommender systems can foster diversity, reduce bias, and promote serendipity in recommendations. This comprehensive approach aims to counteract the negative effects of filter bubbles and offerusers a more enriching and personalized experience.

7.3. Ensemble Approach to Alleviate filter bubbles.

To mitigate the problem of filter bubbles in recommender systems, an ensemble approach can be employed. By combining multiple models, such as the novelty-aware recommender model, diversity-aware model, and other relevant models, recommender systems can generate recommendations that exhibit both diversity and accuracy. This ensemble technique aims to alleviate filter bubble issues while simultaneously improving the overall performance of the recommender system.

The integration of diverse models in an ensemble framework enables the generation of recommendations that gobeyond personalized suggestions, incorporating novel and diverse content. By leveraging the strengths of each individual model, the ensemble approach offers a more comprehensive solution to filter bubbles, enhancing the system's ability to provide users with a wider range of recommendations. Figure 7 depicts a simplified block diagram illustrating the ensemble architecture used in recommender systems.

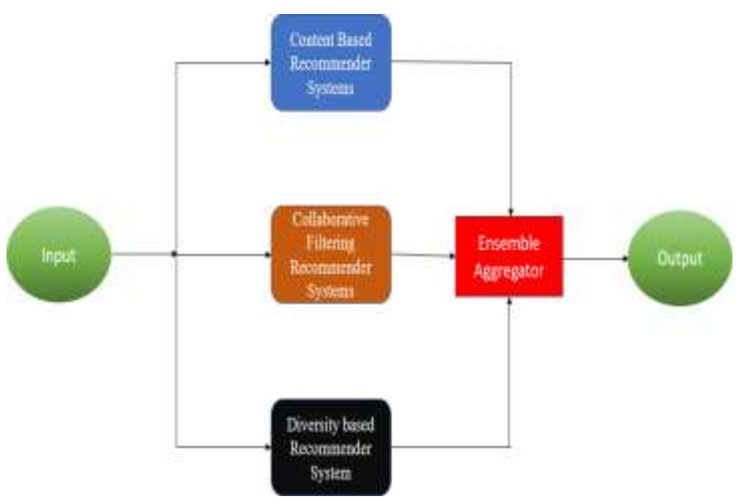

Fig 7: Basic Block Diagram of Ensemble Architecture used in Recommender Systems.

CONCLUSION

In this study, we conducted a systematic analysis of the filter bubble phenomenon in recommender systems. To ensure a comprehensive examination of the topic, we employed a thorough bibliometric analysis, which allowed us to explore relevant terms, identify notable studies, and recognize influential authors in the field. By employing advanced visualization techniques, such as word maps of titles and abstracts from the selected papers, we were able to comprehend the main ideas and developments underlying filter bubbles in recommender systems better. This comprehensive approach not only enhances the reliability and validity of our findings but also provides valuable insights into the current state of research in this area.

Our research began with a comprehensive examination of existing literature surveys conducted on the topic. This was followed by a detailed review of the background literature on recommender systems and filter bubbles. Additionally, we conducted a comprehensive analysis of the datasets commonly employed in the development and evaluation of recommender systems, as well as in the study of filter bubbles. We carefully examined the characteristics and suitability of these datasets in relation to the research objectives. By building upon the insights and knowledge gained from previous surveys and established concepts, we aimed to provide a strong foundation for our systematic analysis of filter bubbles in recommender systems.

Subsequently, we conducted an in-depth exploration of filter bubbles in recommender systems, thoroughly examining a wide range of studies and research conducted in this domain. Our systematic review was structured into two distinct sections, focusing on the identification of filter bubbles as the first part, and investigating the diverse range of studies dedicated to mitigating the impact of filter bubbles as the second part. This approach allowed us to provide a comprehensive analysis of both the existence and potential solutions to the filter bubble phenomenon in recommender systems. In addition, we conducted a thorough examination of different solutions and strategies proposed by researchers, carefully assessing their efficacy and potential impact on mitigating filter bubbles in recommender systems.

Furthermore, we explored open challenges in filter bubbles and proposed solutions for improvement. Hence, by confronting these challenges and conducting further exploration of these proposed solutions, we can make substantial progress in effectively mitigating filter bubbles and improving the Caliber and diversity of recommendations in recommender systems.

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