Understanding Echo Chambers in Recommender Systems: A Systematic Review

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Abstract—**Echo chambers refer to the phenomenon in which individuals are consistently exposed to content that aligns with their existing viewpoints. Over time, this can narrow a user's perspective and make it harder to encounter different opinions. In this systematic literature review, we looked at studies published between 2019 and early 2025 and how they have approached this issue, from understanding the cause, and examining existing detection and mitigation strategies. We went through and organized the main findings, noting patterns in the algorithms used, the role of user behavior, and the influence of the data itself. Several works also suggest ways to introduce more variety into recommendations, aiming to break repetitive exposure. Our review confirms that echo chambers and filter bubbles do exist in recommender systems and that they raise concerns for diversity and fairness. Furthermore, we end by pointing to open questions and possible directions for future work, for both researchers and practitioners.**

Keywords—Echo chamber; recommender systems; filter bubbles; collaborative filtering; systematic literature review

I. Introduction

Since their appearance in the 1990s, recommender systems (RS) have experienced huge evolution, evolving from basic filtering algorithms to complex models that influence user experiences on popular digital platforms. In order to provide recommendations, RS first used content-based filtering, which examined item descriptions. Collaborative filtering was introduced by GroupLens and became the standard method [1].

By introducing item-based collaborative filtering in the early 2000s, Amazon transformed the way suggestions were created by emphasizing item similarities [2], [3]. The use of deep learning in the 2010s was the next significant advancement, enabling recommender systems to recognize involved patterns in user behavior and content. Methods like wide & deep learning models and YouTube's neural networks [4] gained popularity. In order to provide contextual and sequential recommendations based on dynamic user interactions, recommender systems nowadays make use of sophisticated models like transformers [5] and reinforcement learning [6]. The discipline of recommender systems is concentrating on enhancing personalization while simultaneously addressing new issues with transparency, fairness, and diversity as a result of ongoing advancements in deep learning and hybrid models [7], [8].

When people are mostly exposed to information, viewpoints, or content that supports their preexisting preferences or ideas, this is referred to as an "echo chamber". This effect occurs when algorithms use user data to customize suggestions, emphasizing material related to the user's past interactions. Although this customization increases user engagement and pleasure, it also runs the risk of isolating consumers in uniform informational settings. Echo chambers are not a novel idea; they have been thoroughly examined in e-commerce [11], [12], social media [9], [10], and news and media [13]. This phenomenon was first examined by Sunstein, C. R., in the context of political discourse, emphasizing how homogenous societies can be produced and ideas polarized by selective information exposure [14].

According to research [15] on filter bubbles, echo chambers occur in the context of recommender systems when algorithms favor information that is similar to what consumers have already interacted with. The intention behind this selective exposure is to increase user pleasure and engagement; however, it unintentionally reduces the range of information that users can access. Promoting a more informed and well-rounded user base requires both understanding and actively mitigating the effects of echo chambers in recommender systems. The dynamics of algorithmic recommendation and its consequences for information variety have been studied recently in research like [12], [16]. The necessity of creating recommender systems that strike a balance between personalization and the incorporation of varied and possibly difficult content is highlighted by this research. In order to document recent developments and new trends in the industry, this analysis focuses on the last seven years. From an initial pool of 564 papers gathered from top scientific databases such as Scopus, IEEE Xplore, Google Scholar, SpringerLink, ACM Digital Library, and DBLP, 56 peer-reviewed studies published between 2019 and early 2025 were chosen for in-depth research.

In light of this, we provide an organized synthesis that is directed by important research topics, illuminating the primary strategies and techniques used in this field of study. Our contribution to this discussion is a Systematic Literature Review (SLR) conducted to explore strategies for reducing the impact of echo chambers in recommender systems and to identify their existence.

The remainder of this study is structured as follows: Section II provides essential background on recommender systems and the concept of echo chambers. Section III presents the related works on echo chambers in recommender systems and recent AI-driven approaches proposed to mitigate them. Section IV details the research methodology and the guiding research questions. Section V presents the main findings and

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offers a critical analysis of the selected studies, highlighting the presence of echo chambers in recommender systems and evaluating the effectiveness of different mitigation strategies. In Section VI, we discuss the implications of our findings. We explore the overall consequences of echo chambers on user behavior and information diversity, and we identify potential directions for future research to address limitations and challenges identified in the literature. Finally, Section VII concludes the study by summarizing the main insights and discussing potential directions for future research. We summarize the main contributions of our review and suggest approaches for future studies to further explore and mitigate the effects of echo chambers in recommender systems.

II. Background

In this section, a comprehensive overview is presented regarding the two primary areas of research that are directly relevant to this systematic review: recommender systems and the echo chamber problem.

A. Recommender Systems

1) Content-based filtering: This method generates recommendations by focusing on product features and user profiles. It analyzes the attributes of items a user has previously interacted with and suggests similar ones based on these characteristics. Aggarwal et al. provided a comprehensive analysis of content-based approaches and their applications, noting their effectiveness across various domains [17].

2) Collaborative Filtering (CF): One of the most popular techniques in recommender systems, which is predicated on the notion that customers with comparable tastes will appreciate comparable products. It looks at user activity, such as ratings and interactions, to provide personalized predictions. Collaborative filtering is commonly divided into two main types: user-based and item-based. In the user-based approach, the system identifies individuals with similar preferences to the target user and recommends items favored by those individuals. The basic idea is simple: if two people have liked similar things in the past, one is likely to like what the other liked. A prominent early contribution in this domain is the research conducted by Sarwar et al. [18], which applied user-based collaborative filtering to movie recommendations and evaluated its effectiveness in that context. Item-based collaborative filtering, on the other hand, focuses on the relationships between items rather than users. It recommends items that are similar to those the user has liked in the past. This approach calculates the similarity between items based on user interactions and suggests items that are most similar to the ones the user has previously rated highly. An influential paper by Koren et al. [19] demonstrates the effectiveness of item-based collaborative filtering, particularly in handling large-scale datasets and providing accurate recommendations. In addition to these traditional approaches, recent advancements have introduced techniques such as matrix factorization and neighborhood-based methods. Matrix factorization techniques, including Singular Value Decomposition (SVD), decompose the user-item interaction matrix into latent factors to discover hidden patterns and improve recommendations. The work by Koren et al. provides a comprehensive overview of matrix factorization techniques and their application to collaborative filtering [20]. Additionally, approaches that integrate collaborative filtering with other methods, such as hybrid systems, aim to address limitations like data sparsity and cold start problems, enhancing the overall recommendation accuracy [21].

3) Hybrid recommender systems: Combine the advantages of collaborative filtering and content-based filtering to improve recommendation performance. Hybrid systems aim to overcome the limitations of each method, such as data sparsity and limited diversity, by combining multiple strategies. In order to enhance recommendation quality, Liang et al. present a hybrid strategy that combines sentiment analysis with matrix factorization [22]; Burke [21] provides a comprehensive overview of various hybrid techniques and their applications. Hybrid methods combine the strengths of content-based and collaborative filtering, offering a more reliable and comprehensive recommendation experience.

Despite their advantages, these methods encounter substantial limitations, particularly in reinforcing echo chambers, which restrict user exposure to diverse content by continually highlighting existing preferences. In content-based filtering, echo chambers emerge when recommendations are primarily based on a user’s past interactions, resulting in repetitive suggestions that gradually limit exposure to diverse perspectives [48]. The echo chamber effect is amplified by exclusive dependence on historical user and item features, which means that it rarely provides novel or diverse content [23]. Similarly, collaborative filtering perpetuates echo chambers by generating recommendations based on the preferences of similar users. As a result, users are repeatedly exposed to content that caters to the preferences of a small, similar group, resulting in a closed feedback loop. As a result, users encounter content that reinforces their biases, limiting exposure to different viewpoints [18].

Hybrid models may continue to highlight user preferences over diversity in recommendations without deliberate strategies [21]. This would reinforce narrow content patterns and limit diversity. In conclusion, despite their benefits, these strategies underscore the ongoing issue of echo chambers in recommender systems and the need for new approaches that actively promote diverse content and diversify user exposure.

B. Echo Chamber Problem

An echo chamber, also known as filter bubble, is a phenomenon commonly observed in recommender systems, where users with similar beliefs mainly interact with each other, reinforcing shared viewpoints and potentially intensifying those opinions. This concept is likened to an echo chamber where homogeneous views are repeatedly echoed within the group, which can sometimes lead to more extreme beliefs [24]. Echo chambers are feared to exacerbate political polarization and public opinion division [25]. Echo chambers are typically identified through their structural characteristics, such as the density of connections and network homophily, as well as the ideological uniformity of their members [28], [33]. Research utilizing digital trace data has examined these features to understand their role in online political polarization and the spread of misinformation [42], [43], [44]. Although some studies suggest that the existence of echo chambers may be overstated [46], [47], evidence generally shows that users tend to form communities with closely aligned views [45].

III. Related Works

The concept of "echo chambers" in recommender systems has evolved from earlier discussions in communication theory, which examines how individuals seek information that confirms their pre-existing views. Cass Sunstein was one of the first to introduce the term "echo chamber" in his work *Republic.com*, where he expressed concern that online algorithms could create isolated communities of like-minded individuals by limiting exposure to diverse perspectives [14]. This concern grew with the increasing influence of algorithms, as Eli Pariser's in "*The Filter Bubble*" [15], the concept is taken further, showing how personalization in recommender systems, especially on social media, can shape the flow of information to fit individual preferences. Over time, this selective exposure can limit the range of viewpoints users encounter, leading to ideological isolation and creating echo chambers [41].

Additionally, the role of echo chambers in the spread of misinformation became particularly prominent during the COVID-19 pandemic, as demonstrated by Cinelli et al., who analyzed how social media platforms amplified false information through echo chambers during the crisis [28].

From 2023 to 2025, recent studies have deepened our understanding of how recommender systems can shape and reinforce echo chambers, while others have explored ways to counter these effects. Gao et al. [37] showed that short-video platforms such as Douyin and TikTok often trap users in repetitive content loops created by engagement algorithms. Similarly, Duskin and Schäfer [67] found that Twitter's Who-to-Follow feature strengthens social homophily, leading to more polarized online communities. Sharma et al. [71] warned that conversational search tools powered by large language models could unintentionally create new forms of selective exposure, while Iwanaga et al. [73] demonstrated that friend-recommendation algorithms can reproduce echo-chamber structures in social networks. Collectively, these studies highlight that echo-chamber effects emerge from continuous user algorithm feedback loops and that mitigating them requires AI-driven designs that promote diversity and balanced information exposure.

While significant progress has been made in understanding echo chambers and filter bubbles in digital environments, existing systematic literature reviews (SLRs) reveal several limitations. Table I presents a summary of key limitations in notable SLRs and the added value of this study.

This SLR provides significant contributions by bridging the gaps left by previous studies. Unlike earlier reviews, it examines a broad timeline, covering research from 2019 to 2025, ensuring inclusion of the most recent advancements. My work integrates new technologies, highlighting their potential in addressing echo chambers effectively.

TABLE I. Identified Limitations in Existing Echo Chamber Studies

Ref.	Limitation
[52]	Does not address recommender systems and provides limited insights into mitigation strategies.
[53]	This review has several limitations. Many studies do not explicitly address the term "echo chamber" and rely on older approaches that may not reflect recent advances. In addition, the review dates back to 2022, while the field has since experienced rapid, exponential growth.

IV. Research Methodology

A. The Need of an SLR

A systematic literature review (SLR) is a structured and comprehensive way of bringing together what has already been studied on a given topic. In academic research, it helps identify and interpret all relevant work connected to a particular question, field of interest. However, past SLRs on recommender systems in echo chambers have left significant limitations. They have overlooked key studies and recent developments that are essential for a complete understanding, and many have failed to include all the necessary literature. Important areas that were often missing include the use of reinforcement learning and deep learning techniques to address echo chambers.

New research directions are especially important for a fuller picture. These include generative AI to counter polarization and adopting reinforcement learning to encourage more unexpected content. Another emerging strategy is to maximize semantic variety in recommendations as a way to limit echo chamber effects. Unfortunately, many earlier SLRs relied on outdated and incomplete methods, leading to biased conclusions. This review aims to close those limitations by using a variety of sources and adopting more recent, comprehensive research methods.

B. Stages of the SLR

In the field of software engineering, Kitchenham's [30] guidelines offer a clear and practical framework for conducting systematic literature reviews. This approach allows researchers to combine evidence in a way that is both structured and repeatable. As shown in Fig. 1, the process involves several key steps: defining the research questions, preparing a review protocol, performing an extensive literature search, applying predefined inclusion and exclusion criteria to select studies, assessing the quality of those studies, extracting the relevant data, and finally, analyzing and synthesizing the findings.

The systematic literature review (SLR) process is typically organized into three main stages: planning, conducting, and reporting. In the planning stage, the need for the review is established, followed by defining the research questions, keywords, and search terms. Researchers then decide on the information sources, develop study selection criteria, and design data extraction forms. In the conducting stage, the relevant studies are chosen, their quality is evaluated, and the necessary data is extracted and synthesized to draw meaningful conclusions. Finally, in the reporting stage, the findings are analyzed, compiled into a synthesis report, and verified to ensure both accuracy and reliability.

C. Research Objective

The questions and objectives that our SLR will address, as shown in Table II, will focus on understanding the echo chamber phenomenon in recommender systems, evaluating existing mitigation strategies, examining new trends and techniques, and identifying unexplored areas in the literature to guide future research efforts. The objective is to provide a comprehensive and up-to-date understanding of the topic.

We used two distinct search strategies to gather as much evidence as possible when conducting the SLR: ("Echo Chamber" OR "Filter Bubble") AND ("Recommender System" OR "Recommendation System"). Scopus, IEEE Xplore, Google Scholar, SpringerLink, the ACM Digital Library, and DBLP were the first six electronic data sources that we searched automatically. We were able to gather a list of potential candidates thanks to this strategy. These databases were chosen because they contain all high-quality conference proceedings and journals related to recommender systems. Additionally, following best practices for systematic literature reviews (SLRs), we used the snowballing search strategy. This required looking over the bibliographies of relevant papers and utilizing them as a foundation to locate additional relevant literature.

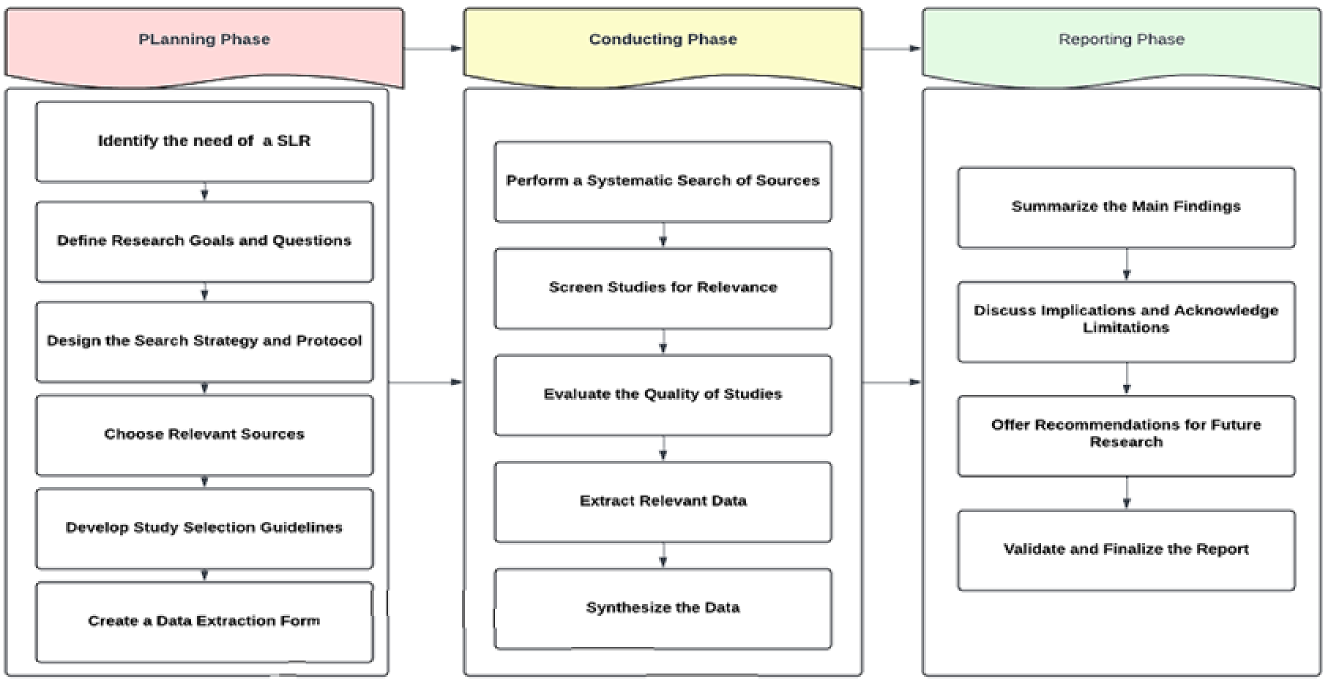

Fig. 1. Key elements of every phase in the SLR.

TABLE II. RESEARCH QUESTIONS

Research Questions	Motivation
RQ1: How echo chamber can be defined and detected in different recommendation approaches?	To comprehend how various recommendation systems create echo chambers. Different types: “collaborative filtering”, “content-based”, and “hybrid” may reinforce user biases in distinct ways. We can find better ways to reduce their impact by defining these.
RQ2: What approaches are implemented to prevent echo chambers in recommender systems, and what techniques are utilized to achieve this	To look into ways to prevent recommender systems from becoming echo chambers. The diversity of recommendations can be increased and users will not be exposed to content that is either biased or repetitive if they are aware of the techniques that work best. We can make recommendations more diverse and improve the user experience by identifying these methods.
RQ3: Have there been any evaluations? If so, what metrics were employed to assess the presence of echo chambers?	To determine whether any evaluations of echo chambers have been carried out. The purpose of this RQ is to identify the metrics used to evaluate the presence of echo chambers.
RQ4: Which datasets were used for evaluating echo chambers?	To identify the datasets commonly used in evaluating echo chambers within recommender systems. Understanding the datasets can provide insights into their suitability and limitations.
RQ5: What are the most promising directions for further research?	To examine the limitations of current solutions and identify future research directions regarding echo chamber and filter bubbles in recommender systems.

D. Selection Process and Eligibility Criteria

We began our selection process by reviewing the studies' titles, publication years, keywords, and abstracts. Then, we applied the criteria outlined in Table III to decide whether each study should be retained for further analysis. Any document that met at least one of the exclusion conditions was discarded.

TABLE III. DETERMINE THE CRITERIA FOR INCLUDING AND EXCLUDING STUDIES

Inclusion criteria	Exclusion criteria
The relevance of each paper was assessed according to its contribution to the five research questions (RQ1 to RQ5).	Papers outside the scope, as they do not focus on RSs
Papers from journals or conferences	Papers that address recommender system but not echo chamber
Papers published between 2019 and 2025	Duplicate papers
Language: written in English	Non-Academic Sources

TABLE IV. QUALITY QUESTIONS

Inclusion criteria	Exclusion criteria	Weight
Are the study's key contributions and motivations stated clearly and precisely?	Yes/partly/no (1/0.5/0)	1
Is the proposed solution clearly explained and feasible for implementation?	Yes/partly/no (1/0.5/0)	1
Did the study clearly define and thoroughly discuss the proposed solution?	- The study provided a high-level overview of the proposed system but lacked in-depth technical details (0.5). - The study offered a clear description of the methodology but limited explanation of its real-world application (1). - The proposed solution is mentioned, but key components are not fully developed or explained (0.5). -The proposed solution is not mentioned or referenced in the study (0).	2
Does the study compare the proposed solution with other existing works?	Yes/partly/no (1/0.5/0)	1
Does the study provide empirical evaluation and present results?	-The study proposed a solution but offered no implementation or evaluation (0). -The study provided an implemented solution but failed to address proper evaluation (0.5). -The study offered a fully implemented and well-evaluated solution. (1).	1,5
Are the study's findings clearly stated?	Yes/partly/no (1/0.5/0)	1

E. Quality Assessment (QA)

To maintain the credibility of our systematic literature review, we assessed the quality of each selected study using a set of predefined questions outlined in Table IV. For each question, responses were scored as 0 (no), 0.5 (partially), or 1 (yes), which allowed us to evaluate how well each criteria was met. Since some questions carried more importance than others, we applied specific weightings accordingly. The overall quality score for each study was then calculated using Eq. (1), combining both the assigned scores and their respective weights.

$$\text{Score} = \sum_{j=1}^{6} \frac{v_j * w_j}{7{,}5} \times 100 \qquad (1)$$

where, w_j the weight assigned to each criterion, reflecting its importance and the value assigned to each quality criterion. Based on our quality assessment, we retained only the studies that scored at or above the average. This process resulted in a final selection of 56 papers for inclusion in our review.

F. Data Extraction Strategy and Synthesis

The relevant information from the final selected papers was documented using the data extraction form shown in Table V. This was done to address the research questions (RQs) outlined in Table IV and to accurately capture the data gathered during the study.

TABLE V. DATA EXTRACTION FORM

Data extraction form
ID, Title, Authors Publication type (Journal/Conference), Publication Year Domain or application feld, Contribution: Findings and Outcomes The study quality assessment **RQ1**.Definition in different recommendation type **RQ2**. Approaches and Techniques used **RQ3**. Evaluation measures and results **RQ4**. Datasets **RQ5**. Limitations & Future work

V. RESULTS

A. Overview of the Selected Studies

After completing the first step of the study selection process, as shown in Fig. 4, a total of 752 publications were retrieved from the Electronic Data Sources (EDS) searches using the search string. The titles of the articles were then checked for duplicates, and 564 candidates remained for further refinement based on the previously explained inclusion and exclusion criteria. The number of research papers to be reviewed in the systematic review was reduced from 564 to 234 after applying the exclusion criteria, and only 56 of these were found to be relevant. An additional six articles were identified by reviewing the reference lists of the relevant papers. Finally, the six quality assessment criteria listed in Table III were applied to ensure that the included findings would contribute valuable insights to the systematic literature review (SLR). Eight papers, including [75] [87] [93] [98] [100] [102] [104] [108], that scored 53.68 or lower, were discarded.

B. Classification of the Selected Studies

In this phase of the research, we investigate the distribution of the selected studies by years of publication, data sources and publication venues.

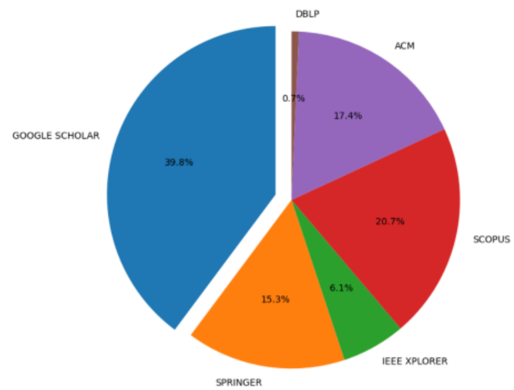

Fig. 2. Distribution by data sources.

Fig. 2 shows the proportion of selected research papers from various data sources. Google Scholar accounts for the largest share, providing 39.8% of the relevant papers, followed by Scopus with 20.7%, and ACM with 17.4%. Springer contributes 15.3%, while IEEE Xplorer and DBLP provide 6.1% and 0.7%, respectively. This distribution emphasizes the importance of Google Scholar and Scopus as major sources for gathering relevant research in this domain.

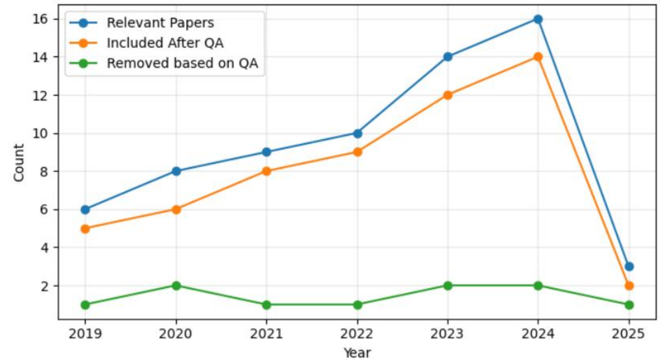

Fig. 3. Distribution of relevant papers before and after QA (2019-2025).

Fig. 3 illustrates the distribution of relevant papers from 2019 to early 2025, highlighting both the papers included after the quality assessment (QA) and those removed based on the QA. The total number of relevant papers increased from 7 in 2019 to a peak of 16 in 2024, showing growing interest in the field. Papers included after QA also rose from 5 in 2019 to 14 in 2024. The number of papers removed during QA fluctuated between 1 and 2 over the same period. In early 2025, both relevant papers and those included after QA dropped to 3 and 2, respectively, while papers removed during QA stood at 2.

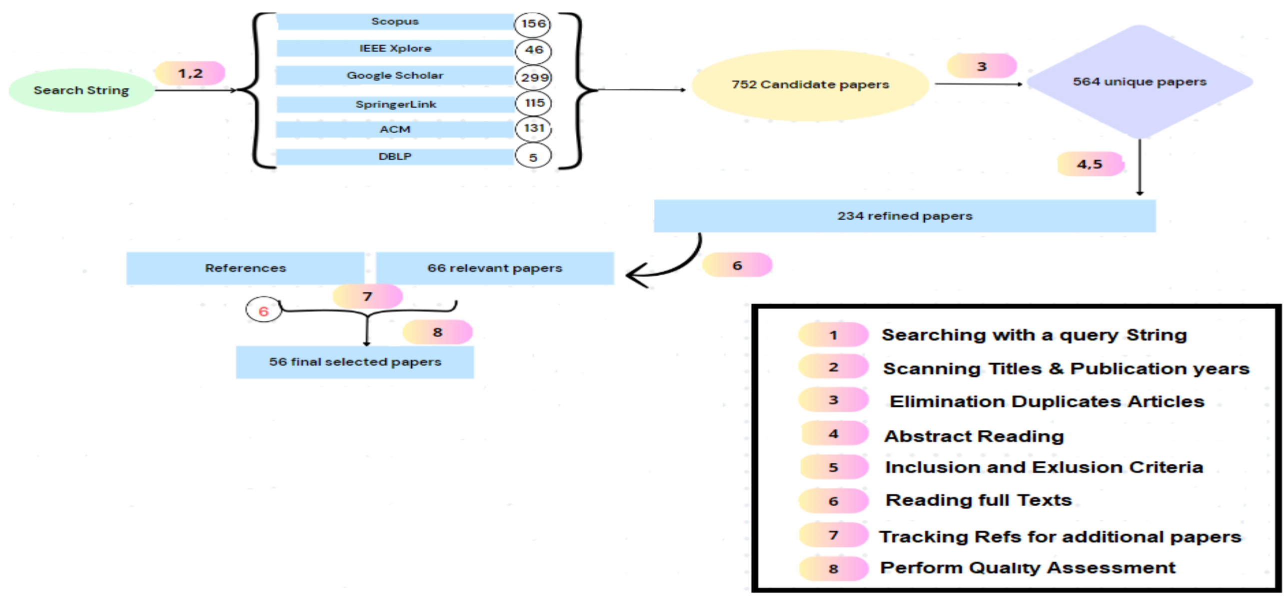

Fig. 4. Summary of the final paper selection process.

C. Data Extraction Results

In the following sections, we will present the findings of this systematic review and analyze them to address the research questions outlined in Section IV.

1) Summary of the RQ1: Echo chambers are a significant concern in various types of recommender systems, each manifesting in distinct ways depending on the underlying algorithm. In collaborative filtering systems, echo chambers arise when users are consistently exposed to content that mirrors their past interactions and the preferences of similar users. This feedback loop intensifies the reinforcement of existing beliefs, leading to a narrowing of perspectives and a reduction in content diversity. The concept of echo chambers in collaborative filtering has been extensively examined in recent literature, highlighting both the mechanisms behind their formation and the implications for user experience. Yingqiang Ge et al. [58] describe an echo chamber as a phenomenon in which users' interests are reinforced through repeated exposure to similar items or categories. This process closely aligns with the principles of collaborative filtering, where user interactions and preferences are analyzed to generate recommendations based on the behavior of similar users. In addition, Ruben Interian et al. highlight the feedback loop embedded in collaborative filtering systems: as user preferences are continually reinforced, individuals are repeatedly exposed to similar content. Over time, this cycle restricts the diversity of perspectives and encourages to echo chamber [31]. Similarly, Sami Khenissi et al. [88] explain that echo chambers often emerge from the algorithmic tendency to recommend content that aligns with a user's previous behavior, gradually narrowing the range of information available to them. Alireza Gharahighehi et al. focus on session-based recommender systems, underscoring how the emphasis on predictive accuracy in collaborative filtering can inadvertently lead to the creation of echo chambers by exposing users to similar content and viewpoints over time [49]. Mert Can Cakmak et al. [107] Defines echo chambers as situations where algorithms repeatedly expose users to similar viewpoints, reinforcing pre-existing preferences. It also discusses detection via analyzing homogeneity in user–item interactions and network-based similarity. Lastly, Vancompernolle Vromman and Fouss [96] provide an experimental analysis, demonstrating that collaborative filtering algorithms naturally reduce content diversity, thereby reinforcing existing user preferences and contributing to the echo chamber effect. A common theme emerges from all of these studies: while collaborative filtering improves user satisfaction through relevant recommendations, it also runs the risk of creating closed content loops that discourage engagement with a wider range of perspectives [15]. Similarly, in content-based filtering systems, echo chambers develop as the algorithm prioritizes content similar to what the user has previously consumed. Antoine Vandelville et al. [40] define an echo chamber in this context as a situation where users are predominantly exposed to content that aligns with their existing beliefs and preferences, leading to a reinforcement of those views. This occurs because content-based algorithms curate and recommend items based on the user's past interactions, often resulting in a narrow range of viewpoints being presented. As users engage with content that reflects their interests, the recommendation system continues to suggest similar content, thereby creating a feedback loop. This can limit exposure to diverse perspectives and opposing ideas, fostering an environment where users remain insulated within their own ideological bubbles. Consequently, echo chambers in content-based systems can hinder open discourse and contribute to the polarization of opinions.

Hybrid recommender systems, which combine elements of both collaborative and content-based filtering, attempt to mitigate some of these issues by balancing accuracy with diversity. However, they are not immune to the creation of echo chambers, particularly if the system overemphasizes content that aligns with the user's established preferences. The challenge with hybrid systems lies in effectively balancing the competing demands of personalization and diversity, which, if not carefully managed, can still lead to the reinforcement of homogeneous content [49, 96]. Given these critiques, it is evident that each type of recommender system has inherent strengths and weaknesses concerning the formation of echo chambers. To mitigate the risks associated with echo chambers, strategies such as introducing diversity and serendipity in recommendations, employing algorithms that balance user exploration with relevance, and ensuring a mix of content that includes both popular and lesser-known items are essential. Additionally, applying fairness metrics to prevent the disproportionate favoring of specific content types can help create a more balanced recommendation environment [12, 62].

The next summary of RQ2 will delve deeper into how these mitigation strategies can be implemented across different recommender systems to reduce the impact of echo chambers, ensuring a more inclusive and diverse content experience for users.

2) Summary of the RQ2: After analyzing how researchers define the echo chamber, we now focus on the review of proposed of proposed approaches in collaborative filtering and other as well as the identification of the techniques used to avoid echo chamber. In the research area of collaborative recommendation and others types, several techniques have been disclosed for avoiding echo chamber. Table VI classifies studies according to techniques used for overcoming echo chamber issues in both collaborative approaches and other.

Collaborative Filtering based approaches leverage user-item interactions to generate recommendations, with several techniques focusing on enhancing diversity to prevent echo chambers. One such technique is the Targeted Diversification VAE-based Collaborative Filtering (TD-VAE-CF), which integrates Variational Autoencoders to inject targeted diversification into the recommendation process [60]. Reinforcement Learning based methods are also applied within CF frameworks, where adaptive learning helps to diversify recommendations over time by considering long-term user satisfaction rather than short-term interests [36], [38], [61]. Another noteworthy CF-based method is the Cross-domain.

Recommendation Model with Adaptive Diversity Regularization, which extends the concept of diversity across different domains, thereby broadening the scope of recommendations beyond a single domain [29]. Additionally, Novel serendipity-oriented RS, Generating Self-Serendipity Preference (GS^2-RS) is designed to introduce serendipitous recommendations, making the user's experience more varied and less predictable [65].

On the other hand, other types of Recommender Systems incorporate approaches that are not strictly based on collaborative filtering but are equally crucial in avoiding echo chambers. The Gini Coefficient Analysis is utilized to measure inequality in the distribution of recommendations, thus ensuring a fairer spread of content exposure across different users [81]. The Community Aware Model [31], [66], [81], [90] focuses on the social aspects of recommendations by accounting for the community structure, which inherently promotes a diversity of perspectives. Techniques like Determinantal Point Process (DPP) provide a probabilistic framework that naturally favors diverse outcomes in recommendation generation [32], [88]. Furthermore, Contrarian Recommendations deliberately suggest items contrary to the user's typical preferences, thereby breaking the cycle of repetitive content exposure [5].

Other advanced approaches include Maximizing Semantic Volume, which aligns with the content-based approach by expanding the semantic range of recommendations. This technique ensures that users are exposed to a broader variety of topics, mitigating echo chambers and enhancing diversity within their content consumption [20, 26]. Similarly, Diversification Approaches for Session-Based Recommenders are often integrated into hybrid approaches, combining elements of content-based and re-ranking strategies to dynamically adjust recommendations during a single user session, maintaining engagement and novelty [20, 26, 49]. Allostatic Regulator introduces an adaptive framework under the content-based approach, balancing content exposure dynamically to ensure a healthy mix of familiar and novel recommendations, further addressing echo chamber concerns [39, 54]. Within the knowledge-based approach, techniques like GeNeG (Generalization via Sentiment and Stance Detection) leverage sentiment and stance analysis to introduce diverse perspectives into recommendations. This method promotes balanced content exposure, directly tackling polarization by presenting varied viewpoints based on explicit content analysis [84]. Similarly, the Point-of-View Diversification Technique falls under the knowledge-based approach, intentionally incorporating content from diverse perspectives to promote diversity and user awareness [51].Content-based approaches also include techniques such as Linguistic Diversity, which identifies and incorporates semantically diverse content into recommendations, and Clustering Models using TF-IDF, which focus on grouping content features to ensure varied exposure [4, 20]. These approaches highlight item-specific attributes to balance user preferences with novel suggestions. Finally, advanced hybrid approaches like the Re-ranking are instrumental in reordering recommendations to maximize diversity and fairness while maintaining relevance [70, 94, 107, 107]. Hybrid approaches effectively leverage advanced techniques such as Multi-Agent Systems with Large Language Models (LLMs) [77] and Counterfactual Interactive Recommender Systems (CIRS) [39] to address echo chambers and enhance user experience through innovative interaction and modeling techniques. These diverse methods underscore the multifaceted strategies being employed to enhance recommendation diversity, ensuring that users are introduced to a more diverse set of content and viewpoints, thus effectively mitigating the risk of echo chambers in recommender systems.

3) Summary of the RQ3: Having discussed the different approaches for mitigate echo chamber, we now proceed to the investigation of how these approaches can be validated. Mathematical metrics play a crucial role in quantifying and evaluating the impact of recommendations on user behavior and content diversity.

Diversity metrics, such as ILD@k and the Gini-Simpson Index, are widely referenced in [80], [85], [99], and [49]. These metrics assess how varied the recommended content is. For ILD@k measures the average dissimilarity of items within a list, while the Gini-Simpson Index evaluates the probability that two items belong to different categories. High diversity metrics indicate that the system is exposing users to a broader range of content, reducing the likelihood of echo chambers by encouraging diverse content consumption.Coverage, discussed in [27], [32], [72], and [80], measures the proportion of the item space that is recommended to users. High coverage implies that a wide range of content is being suggested, which helps prevent echo chambers by ensuring that users are exposed to a variety of content rather than just a narrow subset.

The Precision and Recall metrics, as referenced in [27], [32], [38], [85], and [99], are commonly used to evaluate the accuracy of recommender systems. Precision measures the proportion of recommended items that are relevant, while Recall assesses the system's ability to retrieve all relevant items. While these metrics focus on relevance, there is a need to balance them with diversity metrics to avoid reinforcing echo chambers. High precision and recall alone can sometimes contribute to echo chambers if the recommendations consistently reflect known user preferences without introducing new or diverse content.

NDCG (Normalized Discounted Cumulative Gain), as mentioned in [27], [32], [38], and [60] and defined in Eq. (2) and Eq. (3), evaluates the ranking quality of recommended items, taking into account both relevance and the position of items in the recommendation list. This metric is important for ensuring that while the recommendations are accurate, they also maintain a balance with diversity to prevent the dominance of a narrow set of content. Formally, it is defined as:

$$DCG = \sum_{i=1}^{K} \frac{rel_i}{\log_2(i+1)} \tag{2}$$

$$NDCG = \frac{DCG}{IDCG} \tag{3}$$

where, rel_i is the graded relevance score of the i^{th} item and $IDCG$ is ideal discounted cumulative gain [60].

MAE (The Mean Absolute Error), defined in Eq. (4), computes the deviation between the actual and predicted ratings and RMSE (Root Mean Square Error), defined in Eq. (5), discussed in [82], measures the accuracy of predictions by calculating the square root of the average squared differences between predicted and actual values. While RMSE is primarily focused on accuracy, it is important to consider that overly optimizing for RMSE without attention to diversity can contribute to echo chambers by continuously reinforcing existing preferences.

$$MAE = \frac{1}{n} \sum_{i=1}^{n} \left| p_{i-r_i} \right| \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (p_i - r_i)^2} \tag{5}$$

The Isolation Index (Iso-Index), highlighted in [27] and [72], measures the segregation of users into isolated groups receiving similar recommendations. A high Iso-Index suggests that users are isolated within echo chambers, as they are only exposed to content that aligns closely with their existing preferences.

TABLE VI. TECHNIQUE USED TO MITIGATE ECHO CHAMBERS IN RS

Refs.	Technique used	Type of approach			
		Collaborative	***Hybrid***	***Modeling***	***other***
[5]	Contrarian recommendations				Novelty Based
[20],[40]	Maximizing semantic volume				Content Based
[27]	New Prototype User Controllable RS			✖	
[29]	Cross-domain recommendation model with adaptive diversity regularization	✖			
[32],[88]	Determinantal Point Process (DPP)			✖	
[32]	Contrastive Co-training	✖	✖		
[34]	Clustering Distance-based Method				
[35]	IPS-based sequence recommendation system (IPS-seqRS)	✖			
[36], [43],[99]	Graph neural network: FRediECH				Graph Based
[36], [38], [61],[106]	Reinforcement Learning based method	✖			
[39]	CIRS, a counterfactual interactive recommender system		✖		
[49]	Candidate Item Selection Manipulation Neighbor Selection Manipulation		✖		Content Based
[50]	Multi-Perspective Search Paradigm	✖	✖		Knowledge-Based
[51]	A point-of-view diversification technique	✖			Knowledge-Based
[54]	Allostatic regulator			✖	
[56]	Modified Random Walk Exploration (RWE)				Graph-Based
[60]	Targeted Diversification VAE-based Collaborative Filtering (TD-VAE-CF)	✖			
[65]	Novel serendipity-oriented RS called GS^2-RS	✖			
[66]	RG REC by integrating Generative Artificial Intelligence (GAI)				Generative AI-Based
[70]	Diversity nudges		✖		
[34],[70],[94], [107]	Re-ranking		✖		
[77]	Multi-Agent Systems and Large Language Models (LLMs)				Hybrid/Generative AI-Based
[78]	SSLE framework		✖		
[81]	Gini Coefficient Analysis		✖		Evaluation Metric
[83]	Linguistic Diversity				Content-Based Diversity
[84]	GeNeG (Generalization via Sentiment and Stance Detection)				Knowledge-Based
[86]	A pseudo global social network				Community Detection
[95]	Inverse Propensity Weighting (IPW)	✖			
[97]	New metric based on the homogenization				Evaluation Metric
[103],[55]	Agent-Based Modeling (ABM)				Simulation-Based
[105]	Clustering based model : TF – IDF algorithm (ICDM)				Content Based

Clustering Coefficient, as discussed in [99], measures the degree to which nodes in a network tend to cluster together. High clustering indicates that users are part of tightly-knit communities, which can lead to echo chambers where users are only exposed to content within their group, reinforcing existing viewpoints.

DIS-EUC is mentioned in [27], and defined in Eq. (6). This metric measure the distance between the recommendations of different user groups. Larger distances suggest stronger group segregation and more severe echo chamber effects.

- $d_u \in \mathrm{R}^M$: The distribution over item categories in the recommendations for user u.

- $\bar{g}_u^{-} \in R^M$:: The average distribution over item categories for the original group $\bar{x}$
- $\hat{g}_u \in R^M$: The average distribution over item categories for the target group $\hat{x}$

$$DIS - EUC = dis(d_u, \hat{g}_u) - (d_u, \bar{g}_u) \quad (6)$$

where, $dis(.)$ represents the Euclidean distance.

Finally, NCI (Normalized Clustering Index) and RWC (Relative Weight of Communities), both mentioned in [36], quantify how users are clustered based on similar opinions and the extent to which users are grouped into distinct communities. High values for these metrics indicate strong echo chambers, where users are more likely to interact with like-minded individuals and less likely to encounter diverse perspectives.

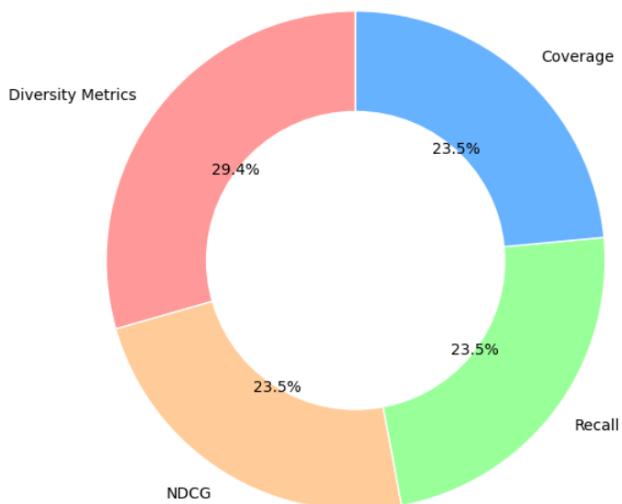

Fig. 5. Proportion of metrics used.

Fig. 5 provides a visual representation of the distribution of metrics used in evaluating recommender systems, particularly in the context of echo chambers. The chart shows that Diversity metrics are the most commonly used, diversity metrics. This distribution suggests a balanced focus on various aspects of recommendation quality, with a particular are also significant but are used slightly less frequently than making up 29.4% of the total. NDCG, Recall, and Coverage metrics each account for 23.5%, indicating that these metrics emphasis on ensuring diversity to combat echo chambers.

4) Summary of the RQ4: The choice of dataset for evaluating echo chamber in recommender systems depends on several factors, including the specific research goals, the characteristics of the recommender system being evaluated, and the availability of suitable data.

Table VII highlights the usage of various datasets in the study of echo chambers in recommender systems. The analysis shows that the MovieLens and Twitter datasets are the most frequently used in research aimed at mitigating echo chambers.

The MovieLens dataset is commonly utilized due to its rich data on user interactions with movies, making it a valuable resource for understanding how recommendation systems can influence user preferences and potentially create echo chambers. Similarly, the Twitter dataset is popular in research because it provides extensive information on social interaction, which is crucial for studying the dynamics of echo chambers in social media environments.

These two datasets play a dominant role in the field, highlighting their central importance in current efforts to investigate the challenges associated with echo chambers in recommender systems. The frequent use of these datasets underscores their importance in developing strategies to ensure that recommendations remain diverse and prevent the reinforcement of narrow user preferences.

Fig. 6 provides a visual representation of the distribution of datasets across different domains in the study of echo chambers in recommender systems. The key observations from the figure are:

Movies represent the most dominant domain, with the largest number of datasets. This suggests that a substantial portion of research on echo chambers focuses on movie recommendation systems, likely due to the widespread use of platforms such as Netflix and MovieLens. The prominence of these systems makes them a key context for examining how echo chambers develop and how they may influence user preferences and viewing habits.

Social media emerges as the second most prominent domain. Given the influence of social platforms on public discourse and user behavior, it is unsurprising that they remain an important focus in studies addressing the dynamics of echo chambers.

E-commerce and News domains each have a moderate representation. This highlights that echo chambers could affect consumer behavior in online shopping platforms and the information people consume from news sources.

Videos, Books, and Music have a smaller but still notable presence in the research. These domains show that echo chamber effects are being studied across various types of content, not just text-based or social media platforms.

Others represents a collection of miscellaneous domains that are less represented individually but still relevant to the overall study of echo chambers.

In summary, Fig. 6 highlights that research on echo chambers in recommender systems is focused on movies and social media with significant attention also given to e-commerce and news platforms. This suggests an interest in understanding how recommendation algorithms influence user behavior across a variety of digital content and platforms.

5) Summary of the RQ5: The last RQ of this SLR addresses future directions on echo chambers in recommender systems. The identified directions suggest various paths to improve how recommender systems function, focusing on mitigating the effects of echo chambers:

TABLE VII. THE DATASETS

Ref.	Dataset	Size of Dataset
[11],[27],[31],[34],[54],[63],[65],],[82],[89],[92],[106],[107]	Movie Lens	6,040 users, 3,702 movies, and 1 million movie ratings [31]: 100,000 ratings of 1682 movies [54] : 6,000 user ratings on 4,000 movies
[26] [40], [62] [81], [85],[90] [99],[107]	Twitter Dataset	[81]: 2.2 million nodes (users), 325.5 million edges (connections), and 3 billion tweets [26]: 2.2 million nodes (users), 325.5 million edges (connections), and 3 billion tweets [40] : 2,414,584 tweets and 7,763,931 retweets from 22,853 Twitter profiles [62]: approximately 217 million tweets
[27]	DIGIX-Video	N/A
	Amazonn-book	N/A
[29]	Douban	N/A
[32]	Amazon Music	Number of Users: 5,541 Number of Items: 3,568 Number of Interactions: 64,706 Number of Categories: 60
	Amazon Sport	Number of Users: 35,598 Number of Items: 18,357 Number of Interactions: 296,337 Number of Categories: 149
[38]	Gowalla	950,327 friend relationships among 196591 users
[38], [60]	Yelp2018	4.7 million user reviews, more than 150,000 merchant profiles, 200,000 images, and 12 metropolitan areas
[39]	Kuai Rec	N/A
[49]	Routana	Number of Sessions: 324,505 Number of Interactions: 5,529,007 Number of Items: 29,641
	Kwestie	Number of Sessions: 297,342 Number of Interactions: 922,680 Number of Items: 22,465
	Globo	Number of Sessions: 1,048,389 Number of Interactions: 2,986,226 Number of Items: 45,559
	Adressa	Number of Sessions: 5,607,303 Number of Interactions: 8,894,565 Number of Items: 27,805
[51]	The Brazilian presidential election	True news : G1: 905 news articles R7: 959 news articles Fake News: LUPA Agency: 78 news articles
[58]	Alibaba Taobao	Accessing logs from 86,192 users over a five-month period, spanning from January 1, 2019, to May 31, 2019.
[59]	-	40,000 news articles and a set of 500 users
[60]	Reddit	N/A
[64]	subset of the TREC Washington Post corpus	728,626 news articles and blog posts from January 2012 through December 2020
[72]	ReDial	N/A
[91]	TG-REDIAL	N/A
[92]	Yelp Challenge	N/A
[97]	Own Dataset	317 users registered in the system, and 221 interacted with the news recommendations

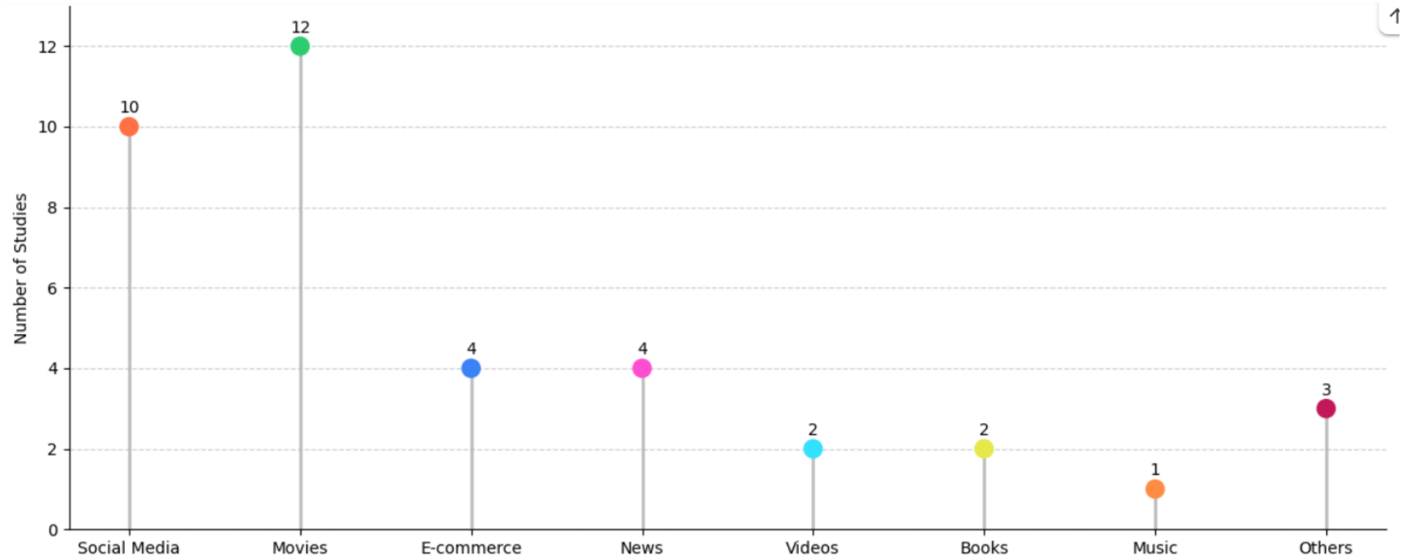

Fig. 6. Count of datasets by domain.

Longitudinal Studies (25%): Conducting long-term studies to track changes in user behavior over time is crucial. Such studies will help understand how echo chambers evolve and the long-term effects of potential interventions [26] [31] [68] [70] [78] [79] [89] [97].

Algorithmic Interventions (15%): Further development and testing of algorithms are necessary to promote diverse viewpoints. These new algorithms will be essential in combating echo chambers by exposing users to a wider range of content [68] [78] [79].

Empirical Validation (5%): A significant direction for future research is the need for more empirical studies that use real-world data from social media platforms to validate computational models. Comparing simulation results with actual user behavior will help determine the real-world impact of echo chambers [55] [69] [79].

Cross-Cutting Content Promotion (5%): Researchers should focus on developing strategies to promote content that bridges different perspectives. Encouraging dialogue between opposing viewpoints is essential for reducing polarization and creating a more balanced user experience [31] [89] [97].

Ethical and Interdisciplinary Approaches (5%): Future research should investigate ethical algorithm design and collaboration across disciplines for a holistic perspective. [26] [76] [78].

User Behavior and Engagement (20%): More research is needed on how users react to diverse content and opposing viewpoints. Understanding user engagement patterns will guide the design of recommender systems that foster more balanced and meaningful interactions [31] [49] [59] [79] [91] [103].

Advanced Technologies and Concepts (15%): Applying AI techniques, like generative AI and deep learning, to improve recommendations [5] [58] [74] [77] [78] [85].

User-Centric Approaches (10%): Designing systems that are tailored to individual users' preferences, behaviors, and feedback will be crucial for creating more personalized and diverse recommendation experiences [26],[78],[89].

An important future direction is the integration of generative AI to enhance content diversity and balance in recommendations. By leveraging generative AI, systems could produce content that represents multiple perspectives or simulate discussions reflecting diverse opinions, fostering a more inclusive and dynamic user experience [74],[101].

VI. Discussion

After following a specific series of detailed steps to collect the most relevant evidence, we now analyze and critique the findings. In addition, Section VI B outlines the limitations of this SLR. A summary of the results for each research question (RQ) is visually presented in the schematic model shown in Fig. 7.

A. *Discussion of Findings*

Research on echo chambers in recommender systems has consistently highlighted their pervasive influence across various recommendation algorithms, including collaborative, content-based, and hybrid systems. A major limitation of collaborative filtering, for example, is its inherent reliance on past user behavior and preferences of similar users. This often leads to feedback loops where users are repeatedly exposed to the same type of content, reinforcing their preferences and restricting their exposure to diverse perspectives. This absence of diversity keeps users in echo chambers, narrowing their content exploration and contributing to polarization [98].

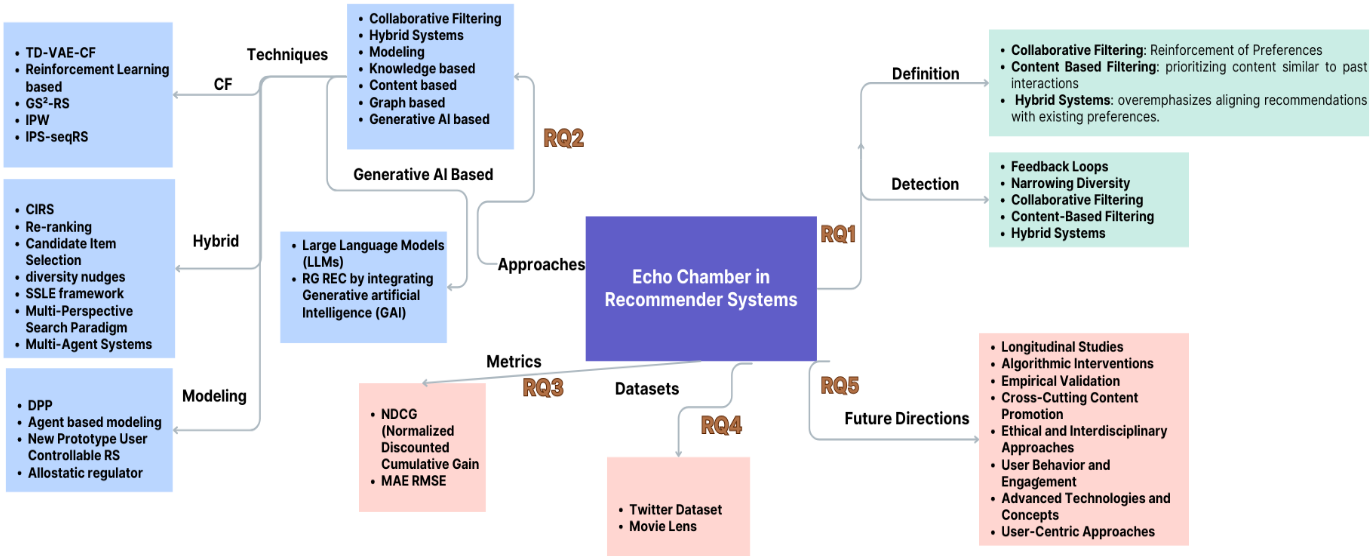

Fig. 7. Overview of findings for the research questions.

To address these limitations, several innovative approaches have been proposed. Targeted Diversification VAE-based Collaborative Filtering (TD-VAE-CF) [60] and Reinforcement Learning-based methods mitigate the feedback loop issue by introducing varied recommendations, diversifying the range of topics and content suggested to users. However, these methods often face challenges in maintaining relevance while enhancing diversity, as balancing the two can sometimes lead to reduce user satisfaction. Community-Aware Models and Contrarian Recommendations attempt to address these issues by integrating social context and intentionally suggesting items that contrast with user preferences. These models break the echo chamber cycle by exposing users to diverse viewpoints and encouraging engagement with content [55]. More advanced approaches, such as the Triple-Filter-Bubble framework utilizing an Agent-Based Model (ABM) [103] tackle systemic challenges like societal fragmentation. ABMs simulate cognitive processes behind echo chambers, including confirmation bias, offering valuable insights into how personalized recommendations contribute to polarization. Yet, their reliance on complex simulations may limit their applicability in real-time systems. Agent4Rec "a recommendation simulator", extends this work by addressing unresolved challenges like causality and user engagement. This approach highlights the importance of understanding the interplay between user behavior and recommendation algorithms, but its use in real-world applications remains questionable [63].

Another valuable direction focusing on maximizing semantic volume and linguistic diversity to enrich content recommendations. Expanding the range of topics and styles, these systems reduce bias and enhance user exposure to new perspectives. RGRec, combining graph-based reasoning, belief nudging, and generative AI, provides an advanced solution by detecting imbalances in user beliefs and nudging users toward diverse content [66]. While the system effectively encourages greater exploration, its reliance on belief manipulation raises ethical concerns about user autonomy. Various scales were used to evaluate these techniques. Diversity Metrics (e.g., ILD, Gini-Simpson Index) are critical for assessing how well systems expose users to a wide variety of content. However, over-reliance on traditional metrics like Precision and Recall, which prioritize accuracy over diversity, can inadvertently reinforce echo chambers. Balancing these metrics with diversity measures remains a key challenge.

Datasets such as MovieLens and Twitter are frequently used to study echo chambers, offering insights into their development across different platforms. However, these datasets primarily focus on entertainment and social media domains, limiting generalizability to contexts like e-commerce or news. Expanding research to incorporate diverse datasets is essential for understanding echo chambers across various sectors.

In summary, while existing methods face challenges such as balancing relevance and diversity or ensuring real-time applicability, newer approaches like graph-based reasoning, semantic diversity, and agent-based simulations offer promising solutions. By addressing these limitations and applying a combination of innovative techniques with evaluation metrics, researchers can more effectively mitigate echo chambers. The continued use of diverse datasets will help ensure that these strategies remain robust and adaptable across multiple domains [40], [66], [83].

B. Limitations of this Systematic Literature Review

A limitation of this review is that, although it covers studies from 2019 to 2025, the analysis only incorporates work published up to early 2025. Any significant research released after this point has not been captured, which may limit the completeness of the findings. Furthermore, despite selecting studies from six major digital libraries, there may still be relevant research from other sources that was not included. The review also focused exclusively on English-language publications, meaning that important non-English studies might have been overlooked. Additionally, due to time constraints, this review relies on self-reported performance results from the authors of the selected studies, which may introduce bias into the assessment.

VII. Conclusion and Future Works

In this SLR, we have selected 56 research papers, published between 2019 and 2025, to explore how echo chambers appear in recommender systems and the solutions proposed to mitigate them. The main strength of this review is the use of a clear and systematic methodology, including a wide search strategy, predefined keywords, and strict inclusion and exclusion criteria. This ensures that the findings are both reliable and comprehensive. The study not only highlights the influence of echo chambers on user experience and content diversity but also evaluates the effectiveness of existing approaches to reduce polarization. Therefore, this work is valuable for guiding both researchers and practitioners, and it can also support the development of recommender systems that balance personalization with exposure to diverse content. Despite these contributions, this review has several limitations. The analysis focused primarily on studies published in English and indexed in major databases, which may exclude relevant non-English or gray literature. In addition, many included studies relied on simulated or single-platform datasets, limiting the generalizability of conclusions about real-world systems.

As a future work, we plan to build this SLR to address these limitations by conducting cross-platform, longitudinal, and user-centered analyses to better capture the dynamic nature of echo chambers. Promising directions include the integration of natural language processing, state space models, and other advanced AI techniques to design adaptive recommenders that maintain personalization while promoting exposure to diverse and balanced content.

References

[1] P. Resnick, N. Iacovou, M. Suchak, P. Bergstrom, and J. Riedl, "GroupLens: An open architecture for collaborative filtering of Netnews," in Proc. ACM Conf. Computer Supported Cooperative Work (CSCW), Chapel Hill, NC, USA, 1994, pp. 175–186.

[2] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques for recommender systems," Computer, vol. 42, no. 8, pp. 30–37, Aug. 2009, doi: 10.1109/MC.2009.263.

[3] A. Töscher, M. Jahrer, and R. M. Bell, "The BigChaos solution to the Netflix Grand Prize," *Netflix Prize Documentation*, 2009, pp. 1–52.

[4] P. Covington, J. Adams, and E. Sargin, "Deep neural networks for YouTube recommendations," in *Proc. ACM Conf. Recommender Systems (RecSys)*, 2016.

[5] F. Sun, L. Yao, and Y. Li, "BERT4Rec: Sequential recommendation with bidirectional encoder representations from transformers," in *Proc. ACM Conf. Recommender Systems (RecSys)*, 2019.

[6] J. Zhao, H. Li, L. Qu, Q. Zhang, Q. Sun, H. Huo, and M. Gong, "DCFGAN: An adversarial deep reinforcement learning framework with improved negative sampling for session-based recommender systems," *Information Sciences*, vol. 596, pp. 222–235, 2022.

[7] P. Törnberg, D. Valeeva, J. Uitermark, and C. Bail, "Simulating social media using large language models to evaluate alternative news feed algorithms," *arXiv preprint*, arXiv:2310.05984, 2023.

[8] C. C. Aggarwal, "A comprehensive survey on recommender systems," 2018.

[9] M. Cinelli, A. Galeazzi, S. Galea, and C. Valensise, "The echo chamber effect on social media: A study of the role of recommender algorithms," *Journal of Computational Social Science*, 2020.

[10] P. Barberá, "How social media reduces mass political polarization: Evidence from Germany, Spain, and the U.S.," 2014.

[11] J. Kim and M. Kim, "The effect of personalized recommendations on consumer behavior: An empirical study of e-commerce platforms," *Electronic Commerce Research and Applications*, 2017.

[12] C. T. Nguyen, "Cognitive islands and runaway echo chambers: Problems for expert dependence," *Synthese*, 2018. doi: 10.1007/s11229-018-1692-0.

[13] C. Vaccari and A. Valeriani, "Echo chambers in online news consumption: Evidence from an experimental study," *Journal of Information Technology & Politics*, 2021.

[14] C. R. Sunstein, *Republic.com 2.0*, Princeton, NJ, USA: Princeton University Press, 2007.

[15] E. Pariser, *The Filter Bubble: What the Internet is Hiding from You*, New York, NY, USA: Penguin Press, 2011.

[16] J. Möller, D. Trilling, N. Helberger, and B. van Es, "Do not blame it on the algorithm: An empirical assessment of multiple recommender systems and their impact on content diversity," *Information, Communication & Society*, vol. 21, no. 7, pp. 959–977, 2018.

[17] C. C. Aggarwal, "A comprehensive survey of content-based recommender systems: Techniques and applications," *ACM Computing Surveys (CSUR)*, 2016.

[18] B. M. Sarwar, G. Karypis, J. A. Konstan, and J. Riedl, "Item-based collaborative filtering recommendation algorithms," in *Proc. 10th Int. Conf. World Wide Web (WWW)*, 2001, doi: 10.1145/371920.372071.

[19] Y. Koren and R. Bell, "Matrix factorization techniques for recommender systems," *Computer*, vol. 38, no. 8, pp. 30–37, 2003, doi: 10.1109/MC.2005.263.

[20] Y. Koren, R. Bell, and C. Volinsky, "Matrix factorization techniques with social regularization for collaborative filtering," in Proc. ACM RecSys, 2010, doi: 10.1145/1864708.1864727.

[21] R. Burke, "A survey of hybrid recommender systems: Techniques and applications," *ACM Computing Surveys (CSUR)*, 2002, doi: 10.1145/582034.582036.

[22] X. Liang, Z. Li, and F. A. Wei, "Hybrid recommender system based on sentiment analysis and matrix factorization," in *Proc. Int. Joint Conf. Artificial Intelligence (IJCAI)*, 2020.

[23] P. Lops, M. de Gemmis, and G. Semeraro, "Content-based recommender systems: State of the art and trends," in *Recommender Systems Handbook*, Springer, 2011, pp. xx–xx.

[24] K. Garrett, "Echo chambers online? Politically motivated selective exposure among Internet news users," *J. Comput.-Mediat. Commun.*, vol. 14, no. 2, pp. 265–285, Jan. 2009.

[25] C. R. Sunstein, "The law of group polarization," *J. Political Philosophy*, vol. 10, no. 2, pp. 175–195, Jun. 2002.

[26] R. Jiang, S. Chiappa, T. Lattimore, A. György, and P. Kohli, "Degenerate feedback loops in recommender systems," in *Proc. AAAI/ACM Conf. AI, Ethics, and Society (AIES)*, New York, NY, USA, 2019, pp. 383–390, doi: 10.1145/3306618.3314288.

[27] W. Wang, F. Feng, L. Nie, and T.-S. Chua, "User-controllable recommendation against filter bubbles," in *Proc. 45th Int. ACM SIGIR Conf. Research and Development in Information Retrieval*, 2022.

[28] M. Cinelli, G. De Francisci Morales, A. Galeazzi, W. Quattrociocchi, and M. Starnini, "The echo chamber effect on social media," *Proc. Natl. Acad. Sci. U. S. A.*, vol. 118, no. 9, Mar. 2021.

[29] J. Sun, J. Song, Y. Jiang, Y. Liu, and J. Li, "Prick the filter bubble: A novel cross-domain recommendation model with adaptive diversity regularization," *Electronic Markets*, pp. 1–21, 2021.

[30] B. Kitchenham and P. Brereton, "A systematic review of systematic review process research in software engineering," *Information and Software Technology*, vol. 55, no. 12, pp. 2049–2075, 2013.

[31] R. Interian, G. Marzo, R. Mendoza, and C. C. Ribeiro, "Network polarization, filter bubbles, and echo chambers: An annotated review of measures and reduction methods," Int. Trans. Oper. Res., vol. 30, no. 6, pp. 3122–3158, 2022.

[32] X. Ma, Q. Hu, Z. Gao, and M. AbdelHady, "Contrastive co-training for diversified recommendation," in Proc. Int. Joint Conf. Neural Netw. (IJCNN), 2022.

[33] K. Garimella, G. De Francisci Morales, A. Gionis, and M. Mathioudakis, "Political discourse on social media: Echo chambers, gatekeepers, and the price of bipartisanship," in Proc. 2018 World Wide Web Conf. (WWW '18), Geneva, Switzerland: IW3C2, 2018, pp. 913–922.

[34] M. J. Alam, I. Hossain, S. Puppala, and S. Talukder, “Combating echo chambers in online social network by increasing content diversity in recommendation,” in Proc. Int. Conf., Sep. 2024, pp. 1–16

[35] C. Zhang, Z. Li, and K. Zhang, "An inverse propensity score framework for breaking filter bubble recommendation," in Proc. IEEE Int. Conf. Control, Electron. Comput. Technol. (ICCECT), 2023.

[36] F. Cinus, M. Minici, C. Monti, and F. Bonch, "The effect of people recommenders on echo chambers and polarization," 2022.

[37] Y. Gao, Z. Wang, J. Li, and L. Zhang, “Echo Chamber Effects on Short Video Platforms,” Proc. Int. Conf. on Web and Social Media (ICWSM), 2023.

[38] Z. Li et al., "Breaking filter bubble: A reinforcement learning framework of controllable recommender system," in Proc. ACM Web Conf., 2023.

[39] C. Gao et al., "CIRS: Bursting filter bubbles by counterfactual interactive recommender system," ACM Trans., 2023.

[40] A. Vendeville, A. Giovanidis, E. Papanastasiou, and B. Guedj, "Opening up echo chambers via optimal content recommendation," in Complex Networks and Their Applications XI, H. Cherifi, R. N. Mantegna, L. M. Rocha, C. Cherifi, and S. Miccichè, Eds. Cham: Springer, 2023, vol. 1077, Studies in Computational Intelligence, pp. 83–94. doi: 10.1007/978-3-031-21127-0_7.

[41] I. B. Dylko, M. A. Beam, K. D. Landreville, and N. Geidner, "Echo chambers in the age of algorithms: Evaluating the impact of personalized news recommendations on ideological isolation," J. Inf. Technol. Politics, vol. 15, no. 2, pp. 81–94, 2018, doi: 10.1080/19331681.2018.1448735.

[42] W. Cota, S. C. Ferreira, R. Pastor-Satorras, and M. Starnini, "Quantifying echo chamber effects in information spreading over political communication networks," EPJ Data Sci., vol. 8, no. 1, pp. 1–13, Dec. 2019.

[43] V. R. K. Garimella and I. Weber, "A long-term analysis of polarization on Twitter," in Proc. Int. Conf. Weblogs and Social Media (ICWSM), vol. 11, no. 1, pp. 528–531, May 2017.

[44] J. K. Lee, J. Choi, C. Kim, and Y. Kim, "Social media, network heterogeneity, and opinion polarization," J. Commun., vol. 64, no. 4, pp. 702–722, 2014.

[45] D. Nikolov, A. Flammini, and F. Menczer, "Right and left, partisanship predicts (asymmetric) vulnerability to misinformation," Harvard Kennedy School Misinformation Rev., 2021. [Online]. Available: https://doi.org/10.37016/mr2020-55

[46] L. Terren and R. Borge-Bravo, "Echo chambers on social media: A systematic review of the literature," Rev. Com. Rhetor., vol. 9, pp. 99–118, Mar. 2021.

[47] E. Dubois and G. Blank, "The echo chamber is overstated: The moderating effect of political interest and diverse media," Inf. Commun. Soc., vol. 21, no. 5, pp. 729–745, May 2018.

[48] E. Bakshy, S. Messing, and L. A. Adamic, "Exposure to ideologically diverse news and opinion on Facebook," Science, vol. 348, no. 6239, pp. 1130–1132, 2015.

[49] A. Gharahighehi and C. Vens, "Diversification in session-based news recommender systems," Pers. Ubiquitous Comput., pp. 1–11, 2021.

[50] M. Zhitomirsky-Geffet, "Turning filter bubbles into bubblesphere with multi-viewpoint KOS and diverse similarity," in Proc. Assoc. Inf. Sci. Technol., 2022.

[51] G. M. Lunardi, "Representing the filter bubble: Towards a model to diversification in news," Lect. Notes Comput. Sci., vol. 2019, 2019.

[52] A. Mahmoudi, D. Jemielniak, and L. Ciechanowski, "Echo chambers in online social networks: A systematic literature review," IEEE Access, vol. 12, pp. 9594–9620, 2024, doi: 10.1109/ACCESS.2024.3353054.

[53] Q. M. Areeb et al., "Filter bubbles in recommender systems: fact or fallacy—a systematic review," Wiley Interdiscip. Rev. Data Min. Knowl. Discov., vol. 13, no. 6, e1512, 2023, doi: 10.1002/WIDM.1512.

[54] N. Henry, M. Pedersen, M. Williams, J. Martin, and L. Donkin, "Reducing echo chamber effects: An allostatic regulator for recommendation algorithms," 2023.

[55] D. Geschke, J. Lorenz, and P. Holtz, "The triple-filter bubble: Using agent-based modelling to test a meta-theoretical framework for the emergence of filter bubbles and echo chambers," Br. J. Soc. Psychol., 2019.

[56] B. Paudel and A. Bernstein, "Random walks with erasure: Diversifying personalized recommendations on social and information networks," in Proc. Web Conf., 2021.

[57] M. McPherson, L. Smith-Lovin, and J. M. Cook, "Birds of a feather: Homophily in social networks," Annu. Rev. Sociol., vol. 27, no. 1, pp. 415–444, 2001.

[58] Y. Ge, S. Zhao, H. Zhou, C. Pei, F. Sun, W. Ou, and Y. Zhang, "Understanding echo chambers in e-commerce recommender systems," in Proc. 43rd Int. ACM SIGIR Conf. Res. Dev. Inf. Retrieval, 2020, pp. 2261–2270.

[59] H. Zhang, Z. Zhu, and J. Caverlee, "Evolution of filter bubbles and polarization in news recommendation," in Proc. Eur. Conf. Inf. Retrieval, 2023.

[60] Z. Gao, T. Shen, Z. Mai, M. Bouadjenek, I. Waller, A. Anderson, R. Bodkin, and S. Sanner, "Mitigating the filter bubble while maintaining relevance: Targeted diversification with VAE-based recommender systems," in Proc. 45th Int. ACM SIGIR Conf. Res. Dev. Inf. Retrieval, 2022, doi: 10.1145/3477495.3531890.

[61] N. Sukiennik, C. Gao, and N. Li, "Uncovering the Deep Filter Bubble: Narrow Exposure in Short-Video Recommendation," in Proc. ACM Web Conf. (WWW '24), 2024, pp. 4727–4735, doi: 10.1145/3589334.3648159.

[62] K. Duskin, J. S. Schafer, J. D. West, and E. S. Spiro, "Echo Chambers in the Age of Algorithms: An Audit of Twitter’s Friend Recommender System," in Proc. 16th ACM Web Science Conf. (WebSci '24), 2024, pp. 11–21, doi: 10.1145/3614419.3643996.

[63] A. Zhang, Y. Chen, L. Sheng, X. Wang, and T. Chua, "On Generative Agents in Recommendation," in Proc. 47th Int. ACM SIGIR Conf. on Research and Development in Information Retrieval (SIGIR '24), 2024, pp. 1807–1817, doi: 10.1145/3626772.3657844.

[64] A. Starke, A. S. Bremnes, E. Knudsen, D. Trilling, and C. Trattner, "Perception versus Reality: Evaluating User Awareness of Political Selective Exposure in News Recommender Systems," in Adjunct Proc. 32nd ACM Conf. on User Modeling, Adaptation and Personalization (UMAP Adjunct '24), 2024, pp. 286–291, doi: 10.1145/3631700.3665189.

[65] Y. Xu, E. Wang, Y. Yang, and H. Xiong, "GS-RS: A Generative Approach for Alleviating Cold Start and Filter Bubbles in Recommender Systems," IEEE Trans. Knowl. Data Eng., vol. 36, no. 2, pp. 668–681, Feb. 2024, doi: 10.1109/TKDE.2023.3290140.

[66] M. Wang et al., "Nudging Towards Responsible Recommendations: A Graph-Based Approach to Mitigate Belief Filter Bubbles," IEEE Trans. Artif. Intell., 2024, doi: 10.1109/TAI.2024.3373392.

[67] J. Duskin and B. Schäfer, “Echo Chambers in the Age of Algorithms: An Audit of Twitter’s Who-to-Follow,” Proc. ACM Conf. on Web Science (WebSci), 2024.

[68] Md. Anwar, G. Schoenebeck, and P. S. Dhillon, "Filter Bubble or Homogenization? Disentangling the Long-Term Effects of Recommendations on User Consumption Patterns," in Proc. ACM Web Conf. (WWW '24), 2024, pp. 123–134, doi: 10.1145/3589334.3645497.

[69] D. Trilling, "Communicative Feedback Loops in the Digital Society," Weizenbaum Journal of the Digital Society, vol. 4, no. 2, 2024, doi: 10.34669/wi.wjds/4.2.4.

[70] N. Mattis, P. Masur, J. Möller, and W. van Atteveldt, "Nudging Towards News Diversity: A Theoretical Framework for Facilitating Diverse News Consumption through Recommender Design," New Media & Society, vol. 26, no. 7, pp. 3681–3706, 2024.

[71] N. Sharma, Q. V. Liao, and Z. Xiao, “Generative echo chamber? Effect of LLM-powered search systems on diverse information seeking,” in Proc. CHI Conf. on Human Factors in Computing Systems (CHI), 2024, pp. 1–17.

[72] Y. Zheng, Z. Chen, J. Qin, and L. Lin, "FacetCRS: Multi-Faceted Preference Learning for Pricking Filter Bubbles in Conversational Recommender System," in Proc. AAAI Conf. Artif. Intell., vol. 38, no. 8, 2024, doi: 10.1609/aaai.v38i8.28794.

[73] M. Iwanaga, K. Sato, and T. Nakajima, "Echo-Chamber Formation by Friend Recommendation Algorithms," Proc. ACM Conf. on Recommender Systems (RecSys), 2025.

[74] X. Zhou et al., "Bee and I Need Diversity! Break Filter Bubbles in Recommendation Systems through Embodied AI Learning," in Proc. 23rd ACM Interaction Design and Children Conf. (IDC '24), 2024, pp. 44–61, doi: 10.1145/3628516.3655802.

[75] S. Nagraj and B. Palayyan, "Personalized E-commerce Based Recommendation Systems Using Deep-Learning Techniques," Int. J. Artif. Intell., vol. 13, no. 1, pp. 610–618, Mar. 2024, doi: 10.11591/ijai.v13.i1.pp610-618.

[76] E. Rodilosso, "Filter Bubbles and the Unfeeling: How AI for Social Media Can Foster Extremism and Polarization," Philos. Technol., vol. 37, art. 71, 2024, doi: 10.1007/s13347-024-00758-4.

[77] J. Y. Sun et al., "See Widely, Think Wisely: Toward Designing a Generative Multi-Agent System to Burst Filter Bubbles," in Proc. CHI Conf. Human Factors in Computing Systems (CHI '24), 2024, Art. no. 484, pp. 1–24, doi: 10.1145/3613904.3642545.

[78] H. Han, C. Wang, Y. Zhao et al., "SSLE: A Framework for Evaluating the 'Filter Bubble' Effect on the News Aggregator and Recommenders," World Wide Web, vol. 25, pp. 1169–1195, 2022, doi: 10.1007/s11280-022-01031-4.

[79] T. Donkers and J. Ziegler, "De-sounding Echo Chambers: Simulation-Based Analysis of Polarization Dynamics in Social Networks," 2023. [Online]. Available: [Exact source or DOI missing].

[80] S. Vrijenhoek and N. Helberger, "Recommenders with a Mission – Assessing Diversity in News Recommendations," in Proc. ECML PKDD 2020 Workshops, 2020.

[81] Q. Grossetti, C. du Mouza, and N. Travers, "Community-Based Recommendations on Twitter: Avoiding the Filter Bubble," Lect. Notes Comput. Sci., vol. 11881, pp. 212–227, 2019.

[82] M. El Khoury Badran, J. B. Abdo, W. Jurdi, and J. Demerjian, "Adaptive Serendipity for Recommender Systems: Let It Find You," in Proc. 11th Int. Conf. Agents and Artificial Intelligence (ICAART), vol. 2, pp. 739–745, 2019.

[83] Sonoda, F. Toriumi, and H. Nakajima, "Improving Recommendation Diversity by Maximizing Semantic Volume," in Proc. 2022 IEEE/WIC/ACM Int. Joint Conf. Web Intelligence and Intelligent Agent Technology (WI-IAT), Niagara Falls, ON, Canada, 2022, pp. 496–503, doi: 10.1109/WI-IAT55865.2022.00079.

[84] M. Alam et al., "Towards Analyzing the Bias of News Recommender Systems Using Sentiment and Stance Detection," in Companion Proc. Web Conf. (WWW), 2022, pp. 448–457.

[85] A. Vivek, M. Yang, and Z. Zhao, "Mitigating Filter Bubbles within Deep Recommender Systems," in Data Science for Social Networks, Atlanta, GA, Dec. 2021. [Online]. Available: http://arxiv.org/abs/2209.08180

[86] F. Bagnoli, G. de Bonfioli Cavalcabo, B. Casu, and A. Guazzini, "Bubble Effect Induced by Recommendation Systems in a Simple Social Media Model," Stud. Comput. Intell., vol. 1016, pp. 124–131, 2022.

[87] Y. Ge, S. Zhao, H. Zhou, C. Pei, F. Sun, W. Ou, and Y. Zhang, "Deconstructing the Filter Bubble: User Decision-Making and Recommender Systems," in Companion Proc. Web Conf. (WWW), 2020, pp. 448–457.

[88] S. Khenissi, M. Boujelbene, and O. Nasraoui, "Theoretical Modeling of the Iterative Properties of User Discovery in a Collaborative Filtering Recommender System," in Proc. 14th ACM Conf. Recommender Systems (RecSys '20), 2020.

[89] D. Kalimeris, S. Bhagat, S. Kalyanaraman, and U. Weinsberg, "Preference Amplification in Recommender Systems," in Proc. ACM SIGKDD Int. Conf. Knowledge Discovery and Data Mining, pp. 805–815, 2021.

[90] Q. Grossetti, C. Du Mouza, N. Travers, and C. Constantin, "Reducing the Filter Bubble Effect on Twitter by Considering Communities for Recommendations," Int. J. Web Inf. Syst., vol. 17, no. 6, pp. 728–752, 2021

[91] A. De Biasio, M. Monaro, L. Oneto, L. Ballan, and N. Navarin, "On the problem of recommendation for sensitive users and influential items: Simultaneously maintaining interest and diversity," Knowl.-Based Syst., 2023.

[92] H. Xia, K. Huang, and Y. Liu, "Unexpected interest recommender system with graph neural network," Complex Intell. Syst., 2023.

[93] L. Michiels, J. Leysen, A. Smets, and B. Goethals, "What are filter bubbles really? A review of the conceptual and empirical work," in Adjunct Proc. 30th ACM Conf. User Modeling, Adaptation and Personalization (UMAP '22 Adjunct), New York, NY, USA: ACM, 2022, pp. 274–279.

[94] Y. Peng, X. Qian, and W. Song, "A Re-ranking Approach for Two-sided Fairness on Recommendation Systems," ACM Int. Conf. Proc. Ser., 2023.

[95] JJ. Wu, B. Yang, R. Mao, and Q. Li, "Popularity-aware sequential recommendation with user desire," Expert Syst. Appl., vol. 237, 2024, doi: 10.1016/j.eswa.2023.121429..

[96] F. V. Vromman and F. Fouss, "Filter bubbles created by collaborative filtering algorithms themselves, fact or fiction? An experimental comparison," ACM Int. Conf. Proc. Ser., 2021.

[97] G. M. Lunardi, G. M. Machado, V. Maran, and J. P. M. de Oliveira, "A metric for Filter Bubble measurement in recommender algorithms considering the news domain," Appl. Soft Comput. J., 2020.

[98] A. Godinot and F. Tarissan, "Measuring the effect of collaborative filtering on the diversity of users' attention," Appl. Netw. Sci., vol. 8, no. 1, p. 9, 2023.

[99] A. Tommasel, J. M. Rodriguez, and D. Godoy, "I Want to Break Free! Recommending Friends from Outside the Echo Chamber," in Proc. 15th ACM Conf. Recommender Syst. (RecSys), 2021, pp. 23–33.

[100] R. Qin, B. Mac Namee, and R. Dong, "The Influence of Media Bias on News Recommender Systems," in Proc. 31st ACM Conf. User Modeling, Adaptation and Personalization (UMAP '23), 2023, pp. 301–305, doi: 10.1145/3565472.3595619.

[101] L. Pappalardo et al., "A survey on the impact of AI-based recommenders on human behaviours: methodologies, outcomes and future directions," arXiv preprint arXiv:2407.01630, 2024.

[102] S. C. Matz, "Personal echo chambers: Openness-to-experience is linked to higher levels of psychological interest diversity in large-scale behavioral data," J. Pers. Soc. Psychol., vol. 121, no. 6, pp. 1284–1300, 2021, doi: 10.1037/pspp0000324.

[103] T. Donkers and J. Ziegler, "The Dual Echo Chamber: Modeling Social Media Polarization for Interventional Recommending," 2021.

[104] Y. Jeon, B. Kim, A. Xiong, D. Lee, and K. Han, "Chamber Breaker: Mitigating the Echo Chamber Effect and Supporting Information Hygiene through a Gamified Inoculation System," 2021.

[105] V. S. Chaitanya, M. Mohan and P. S. Thilagam, "A Clustering-based model for the Generation of Diversified Recommendations," 2022 IEEE Silchar Subsection Conference (SILCON), Silchar, India, 2022, pp. 1–6, doi: 10.1109/SILCON55242.2022.10028791.

[106] L. Bojic, "A Novel Model for Diversifying AI-Based Recommender Systems for Societal Well-Being," ESWC 2025 Workshops and Tutorials Joint Proceedings, CEUR Workshop Proceedings, 2025, pp. 1–15

[107] M. C. Cakmak and N. Agarwal, "Influence of symbolic content on recommendation bias: analyzing YouTube's algorithm during Taiwan's 2024 election," Applied Network Science, vol. 10, no. 23, 2025, doi: 10.1007/s41109-025-00713-y.

[108] F. Lomonaco, D. Taibi, V. Trianni, G. Donabauer, and D. Ognibene, "Yes, echo-chambers mislead you too: A game-based educational experience to reveal the impact of social media personalization algorithms," in Commun. Comput. Inf. Sci. (CCIS), vol. 1779, pp. 330–344, 2023.