

Are We Studying the Same Filter Bubble? A Conceptual Framework of the Empirical Literature

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Abstract

Since its introduction, the “filter bubble” concept has sparked extensive multidisciplinary research, yet empirical studies differ substantially in how they define, observe, and operationalize the phenomenon. This conceptual ambiguity makes it difficult to compare findings or synthesize evidence across studies. In this paper, we examine how filter bubbles have been operationalized in the empirical literature. Drawing on a grounded theory analysis of 40 empirical studies, we inductively derive a conceptual framework that distinguishes the components involved in filter bubble formation, the information exchanges between them, the components in which filter bubbles are observed, and the components that shape or mitigate them. Applying this framework, we identify three recurring archetypes of filter bubble operationalization: the algorithmic exposure bubble, the user-behavior-narrowing bubble, and the preference-reinforcement bubble. These archetypes show that empirical studies often examine different phenomena under the same label. The framework provides a structured vocabulary for categorizing existing studies, clarifying the relationship between filter bubbles and adjacent concepts such as echo chambers, and identifying theoretical and methodological blind spots in the current literature.

Keywords

Recommender Systems, Filter Bubble, Literature Review, Grounded Theory

1. Introduction

Fifteen years ago, Eli Pariser published his book *The Filter Bubble: What the Internet Is Hiding from You*, in which he warned that *personalization filters* create “a unique universe of information for all of us — a filter bubble — which fundamentally alters the way we encounter ideas or information” [1]. Since then, the filter bubble has sparked both widespread public concern and sustained academic interest [2]. Researchers from several disciplines have engaged with the phenomenon, both conceptually and empirically, ranging from information law to recommender systems research [3, 4].

At a conceptual level, however, the filter bubble has been heavily criticized for being poorly defined and conceptually ambiguous [2]. In his book, Pariser [1] uses the term to describe several related but distinct concerns. For example, he warns that “personalization filters serve up a kind of invisible autopropaganda, indoctrinating us with our own ideas” (p. 13), that “in the filter bubble, there’s less room for the chance encounters that bring insight and learning” (p. 13), that “the filter bubble tends to dramatically amplify confirmation bias” (p. 51), and that “if a piece of news is about sex, power, gossip, [...] we are likely to read it first. This is the content that most easily makes it into the filter bubble” (p. 14). These examples illustrate that Pariser’s filter bubble is as much about a loss of serendipity and discovery as it is about autopropaganda, confirmation bias, or the amplification of attention-grabbing content. Moreover, his anecdotal account foregrounds anticipated outcomes and dangers, while leaving the question of how such filter bubbles may arise and manifest comparatively underspecified. Against this

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background, it is unsurprising that empirical studies of filter bubbles have often produced contrasting findings [2, 5]. Researchers seeking to study the phenomenon empirically have had to introduce their own interpretations and operationalizations of the filter bubble [2]. As a result, the literature is heterogeneous not only in its findings but also in what it actually studies when it claims to study “the filter bubble”, severely limiting comparability between studies and making evidence synthesis difficult.

Previous research, including our own, has responded to this conceptual ambiguity by proposing more precise definitions of the filter bubble [5, 3, 2]. These definitions clarify what filter bubbles are and are not, thereby sharpening the conceptual boundaries of the concept, distinguishing it from related phenomena such as the echo chamber, and providing a broad but solid foundation for empirical study. At the same time, they leave the question of how filter bubbles are theorized to emerge comparatively open. This paper addresses this question.

To do so, we turn to the empirical literature and leverage the very heterogeneity that has hindered evidence synthesis. To translate Pariser’s broad, anecdotal concerns about personalization into measurable, observable constructs, empirical researchers had to decide where the filter bubble manifests and can be observed, which components of the information environment are involved, and which information exchanges contribute to its emergence. In other words, the empirical literature provides a detailed account of how filter bubbles could emerge.

Building on this insight, we inductively derive an empirically grounded conceptual framework that captures how filter bubbles have been operationalized in the literature. In particular, the framework details (1) the components involved, (2) how information is exchanged between them, (3) where filter bubbles are expected to manifest, and (4) which components are treated as impacting their formation or mitigation.

Based on this conceptual framework, we identify three archetypes of filter bubbles: the *Algorithmic Exposure Bubble*, the *User-Behavior-Narrowing Bubble*, and the *Preference-Reinforcement Bubble*. We relate these archetypes to prior conceptual work and later demonstrate how they can be used to categorize the empirical literature, enabling more meaningful synthesis. Furthermore, we uncover where the echo chamber and filter bubble overlap, and where they differ. Finally, we highlight an important limitation of the empirical literature: a dominant focus on the algorithm.

2. Related Work

As mentioned previously, the filter bubble has generated sustained research interest. While a complete overview of the empirical literature is beyond the scope of this paper, we want to highlight some aspects that informed our research design. Firstly, we note that studying filter bubbles has been a multidisciplinary endeavor, with many contributions from computer science [6, 7, 4], but also social sciences [8], psychology [9], and even physics [10]. To obtain a representative sample of the full spectrum of empirical studies on filter bubbles, it is therefore important to run a multidisciplinary search across diverse literature databases. Second, we note that the computer science community, especially, has focused not only on assessing filter bubbles, but also on mitigating them, e.g., [4]. As we aim to build a comprehensive framework of how filter bubbles have been operationalized, we include mitigation studies in our sample and analysis.

Next, we discuss relevant conceptual and synthesis work. As mentioned previously, several works have sought to address the conceptual ambiguity surrounding filter bubbles by proposing clearer definitions, often explicitly distinguishing the filter bubble from related phenomena, e.g., [3, 5, 11, 2]. Zuiderveen Borgesius et al. [3] distinguish the filter bubble (pre-selected personalization by algorithms) from selective exposure (self-selected personalization by users). Bruns [5] demarcates the differences between the filter bubble and the echo chamber. Dahlgren [11] on the other hand emphasizes the parallels between selective exposure, echo chambers, and filter bubbles. In our own prior work, we built on Dahlgren’s work to propose an operationalized definition of the technological filter bubble. A key difference between these prior works and this work is that they all aimed to clarify conceptually what the filter bubble is and is not, whereas we focus here on how filter bubbles are theorized to arise

in the empirical literature. To conclude our discussion of the conceptual work, we note that in our prior work, we observed that conceptualizations of the filter bubble are often left implicit, i.e., authors do not provide (or refer to) concrete definitions of the filter bubble, but rather use the term abstractly and then proceed directly to operationalization. Because of this, we focus our analysis of the literature on how the filter bubble has been operationalized.

Moving on to synthesis work, we find that prior (systematic) reviews of the empirical literature on filter bubbles have often deliberately included related concepts – primarily, the echo chamber – in their literature searches, e.g., [12, 13], because they are so often used interchangeably. Nevertheless, these same reviews also highlight the importance of distinguishing between the two terms and emphasize the relationship between filter bubbles and personalization algorithms [12, 13], i.e., hypothesizing the role of algorithmic curation in the emergence of filter bubbles. Here, we deliberately focus our literature search on the term “filter bubble”. The results may therefore include both papers exclusively focused on studying the filter bubble and those that study the filter bubble and other related concepts. This will allow us to build a comprehensive conceptualization of the filter bubble, which can later be used to identify where it overlaps with or differs from related concepts, such as the echo chamber. Furthermore, we note that these reviews are primarily focused on evidence synthesis. We highlight Hartmann et al. [13]’s review of echo chambers (which included works on filter bubbles), which emphasizes how differing conceptualizations and operationalizations yielded different outcomes and contrasting results. Their findings illustrate the importance of categorizing the literature based on their operationalization of the filter bubble before synthesizing evidence. Here, we will derive three archetypes from the conceptual work that represent common patterns in operationalization.

3. Methodology

The goal of this paper is to derive a conceptual framework of how filter bubbles are operationalized in the empirical literature. Because this empirical literature spans multiple fields of study and is highly heterogeneous in its approach to filter bubbles, an inductive qualitative approach is needed. We draw inspiration from our work on experienced serendipity in recommender systems [14] and adopt grounded theory methodology (GTM). This approach is well-suited to our purpose because it allows conceptual categories to emerge through iterative comparison across studies, making it appropriate for a conceptually ambiguous and operationally diverse body of research such as the empirical literature on filter bubbles.

However, unlike Binst et al. [14], we apply grounded theory to the empirical literature rather than their interview data. Therefore, we adopt the procedure proposed by Wolfswinkel et al. [15], which consists of four stages: define, search, select, and analyze. Below, we describe how these stages were applied in our research.

In the **define** stage, we specified the scope of our literature search, selected the databases, formulated the search query, and established inclusion and exclusion criteria. Our scope is the empirical literature on filter bubbles, in all its diversity, from the publication of Pariser’s book in 2011 until the end of 2024¹. To capture the multidisciplinary nature of the literature, we searched both computer science databases (ACM Digital Library, IEEE Xplore) and multidisciplinary databases (Scopus, Web of Science). The search query was built around two concepts: filter bubble and personalization. For the first concept, we used only the term “filter bubble(s)”, consistent with our explicit focus on filter bubbles, excluding related concepts such as echo chambers and selective exposure. For personalization, we included a broader set of terms reflecting how different fields refer to the concept, including “recommendation”, “recommender”, “personali(z/s)ation”, “personali(z/s)ed”, “algorithm(ic/s)”, and “exposure”. We will describe the exact inclusion and exclusion criteria in the paragraph on the select stage to avoid unnecessary repetition.

During the **search** stage, this query was executed across the four databases, yielding 961 papers. After deduplication, we retained 626 papers.

¹Note: Papers published after 2024 were coded as part of the stability check later.

In the **select** stage, records were screened against the inclusion and exclusion criteria. In a first selection step based on paper metadata, title, and abstract, studies were included if they were peer-reviewed research papers, written in English, focused on filter bubbles, and contained an empirical element, and were excluded if they did not focus on recommender systems. After this step, 313 papers remained. We then performed a second selection step based on the entire paper content to resolve ambiguous cases. In addition to the previous criteria, studies were also excluded if they primarily examined consequences of presumed filter bubbles, rather than the filter bubble itself. After this step, 116 papers remained. Detailed documentation of the search and selection procedures is available in the [supplementary material on Zenodo²](#).

In the **analyze** stage, we proceeded to coding and analysis. Importantly, we did not code all papers in the relevant literature sample, as our goal was not to present a systematic literature review but to develop a comprehensive conceptual framework. Consistent with GTM, analysis proceeded iteratively through theoretical sampling of datapoints (i.e., papers) and multi-stage coding until additional papers no longer yielded substantively new aspects of filter bubble operationalization.

Coding followed three stages, consistent with Urquhart [16]: open, selective, and theoretical coding. In open coding, we identified and labeled extracts reflecting aspects of filter bubble operationalization, including where it was observed, which components of the information environment were involved, and which information exchanges were presumed to contribute to its emergence or mitigation. In selective coding, these initial codes were organized into higher-level categories, and the main dimensions of variation across studies were identified. In theoretical coding, these categories were related to one another and integrated into a coherent conceptual framework, allowing broader recurring constellations of components, observations, and mechanisms to be understood as distinct archetypes of filter bubbles.

Sample selection proceeded in parallel with coding through theoretical sampling [16]. Rather than aiming for statistical representativeness, theoretical sampling seeks to elaborate, contrast, and saturate emerging categories by selecting analytically informative data points. We conducted four rounds of sampling, analyzing ten papers in each round, for a total of 40 papers. The complete list of coded papers, together with descriptive statistics of the coded set and visualizations of the framework applied to the coded papers, is provided in the [supplementary material on Zenodo²](#). In the first round, papers were selected fully randomly, as recommended for grounded-theory-based literature analysis [15]. This initial analysis revealed two broad types of empirical studies: assessment studies and mitigation studies. Because these appeared to differ substantially in how they operationalize filter bubbles, we restricted the second round to mitigation studies in order to elaborate on this part of the framework. After the second round, we observed a bias toward computer science research and therefore used the third round to sample exclusively from other disciplines. At this point, we found that only the context was not fully saturated, so we sampled another 10 papers that model context to further saturate it.

By the end of the fourth round, we concluded that the analysis had reached theoretical saturation, as no substantively new concepts emerged. To further support this conclusion, we conducted a stability check to determine whether the framework was sufficiently well developed to accommodate new material without requiring conceptual revision. To do so, the lead author first produced a full written specification of the framework, making the final categories and their definitions explicit. This specification was then independently applied by another author to a set of 7 papers on filter bubbles published after 2024, which we term the ‘validation set’. The complete list of validation papers, together with visualizations of the framework applied to the coded validation set, is provided in the [supplementary material on Zenodo²](#). As this stability check yielded no further changes to the framework, it provided additional confidence that the main categories were sufficiently developed and that theoretical saturation had been reached.

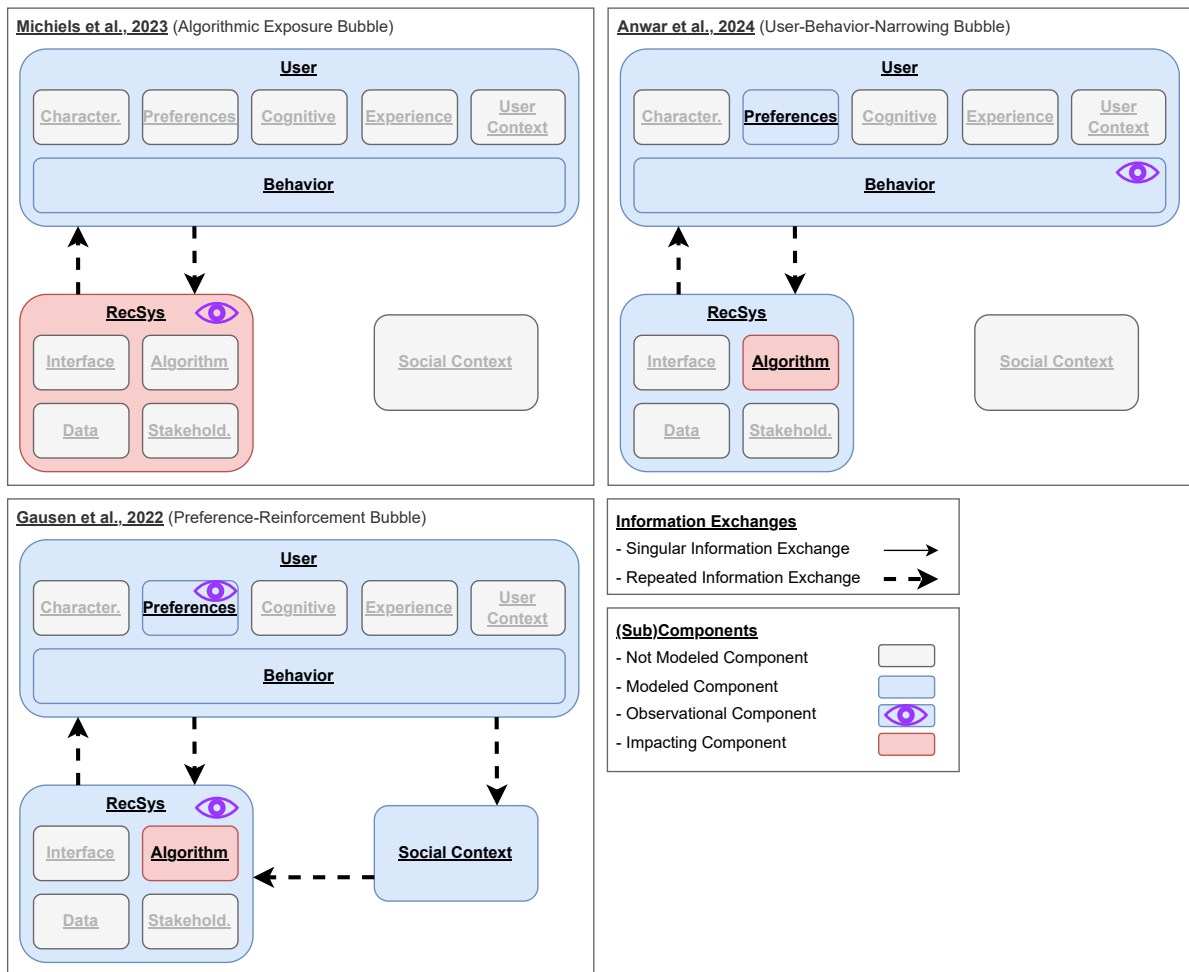


Figure 1: Conceptual framework applied to three case studies, illustrating the archetypes of filter bubble operationalization.

4. Conceptual Framework

Based on our grounded theory analysis, we develop a conceptual framework capturing how filter bubbles are operationalized in the empirical literature. At the highest level, we identify three key **Components** involved in the filter bubble phenomenon: the **User**, the **Recommender System**, and the **Social Context** (Section 4.1). Both the **User** and the **Recommender System** are further elaborated into sub-components, e.g., the *User Behavior*, *Preferences*, or *Characteristics*. Then, inspired by systems thinking [17], we identify **Information Exchanges** between these high-level components (Section 4.2), such as when items are recommended to a user (RecSys → User) or behavioral feedback is sent back to the recommender system (User → RecSys). Together, these components and exchanges describe the information environment in which filter bubbles are studied. We then move from this underlying model to the empirical study of filter bubbles by identifying the **Observational Components** (Section 4.3), i.e., the locations where filter bubbles are expected to manifest and be measured, and the **Impacting Components** (Section 4.4), i.e., the factors that are varied or manipulated to assess or mitigate their formation. A visual representation of the framework is provided in Figure 1. Finally, we show how the framework can be used to categorize empirical studies by how they operationalize filter bubbles, using three case studies to illustrate three distinct archetypes of filter bubble operationalization (Section 4.5).

²<https://doi.org/10.5281/zenodo.20036303>

4.1. Components

Components denote the high-level elements of the information environment that empirical studies treat as relevant to filter bubble formation, observation, or mitigation. Because the **User** and the **Recommender System** are often modeled in greater detail, both are further elaborated into sub-components. We note that, while the empirical literature on filter bubbles varies in scope, the **User** and the **Recommender System** component are explicitly modeled in all sampled studies and, as such, can be considered the core components of information environments in which filter bubbles emerge. In contrast, the **Social Context** was present in about half of the studies. Below, we discuss all three components in detail.

4.1.1. Recommender System

The **Recommender System** is a personalized filtering tool that guides users to relevant items within a large space of options [18]. Studies frequently treat the recommender system as a single monolithic entity, analyzing the platform’s observable outputs without mention of its sub-components [19, 20, 6]. This approach is standard in audit studies of proprietary platforms (e.g., YouTube [7] or Google News [21]). Alternatively, when studies disentangle the recommender system to isolate specific points of influence, it can be seen as a composite of four distinct sub-components.

Algorithm The logic and technical methods used to process input data to rank, select, and filter content (e.g., collaborative [10] or content-based filtering [22]). It defines *how information is filtered*, operating independently from presentation, and is the most frequently isolated sub-component in the literature [23, 24, 10, 25, 26, 27, 4, 28, 9, 29, 30, 31, 32, 33, 34, 35, 36, 37, 8, 38, 22, 39]. To assess filter bubble formation, studies often compare fundamentally different recommendation logic—such as Gausen et al. [28] testing chronological versus popularity-based curation—or systematically fine-tune internal parameters, as in Bellina et al. [10], adjusting similarity and popularity biases to observe the resulting user rating distributions. For mitigation, researchers frequently propose novel algorithms. For instance, Anwar et al. [23] test diversity-oriented heuristics, and Wang et al. [22] propose a new nudging strategy to gradually shift user interests.

Interface The front-end presentation layer and set of affordances (e.g., scrolling, clicking) that render algorithmic outputs perceivable and actionable. It dictates *how the recommendation is presented and interacted with*, shaping user experience without changing the underlying recommendation logic. Several studies isolate this component to examine its specific role in the filter bubble [26, 40, 27, 7, 32, 33, 41, 42]. To assess its role in bubble formation, Bharadhwaj and Srivastava [26] isolate the presentation layer by comparing user browsing behavior when a browser’s “new tab” displays algorithmic recommendations versus a blank page. For mitigation, researchers frequently manipulate the interface to break the bubble through transparency and agency. For instance, Kunkel et al. [33] and Nagulendra and Vassileva [41] evaluate interactive visual dashboards and control panels that expose the underlying recommendation mechanisms, while Tintarev et al. [42] use profile visualizations to explicitly highlight user “blindspots.”

Data The underlying corpus of items, user histories, and metadata signals that determines *what information is available* to the system, directly constraining the algorithm’s learning capabilities and recommendation options. The data sub-component is isolated across several studies [43, 23, 24, 25, 4, 31, 34, 38, 22]. Experimental interventions often alter the structural connectivity or availability of this information. For instance, Jiang et al. [31] adjust the size and growth rate of the set of items eligible for recommendation to limit the emergence of extreme user preferences over time. Similarly, Ali et al. [43] manipulate the data corpus by running distinct types of political ad campaigns (e.g., neutral voting information versus issue-based ads) to observe how platform delivery differs across these content types.

Stakeholders Entities (e.g., editors or administrators) that actively intervene in the recommendation flow. It specifies *who can intervene in the recommendation process*, capturing dynamic influence distinct from static design decisions made prior to implementation. Stakeholder influence is explicitly isolated in a subset of the literature [43, 25, 27, 34, 44]. For example, Bountouridis et al. [27] operationalize this by modeling “editorial priming,” giving content providers direct control over which news articles are promoted. Furthermore, Berman and Katona [25] explicitly model the platform as a stakeholder whose objective is to maximize long-term ad revenue through manipulating filtering algorithm parameters, demonstrating how these overarching business goals dictate which filtering algorithms are deployed.

4.1.2. User

The **User** represents the entity that initiates interaction, processes recommendations, and provides feedback to the system. The framework breaks the user down into six sub-components:

Behavior The observable actions, interactions, and engagement patterns (e.g., clicks, viewing time, purchases) exhibited while interfacing with the system. It defines *what the user actually does*, functioning as the raw feedback signal that triggers future system outputs. User behavior is isolated across a wide range of studies [43, 23, 10, 25, 26, 27, 20, 6, 38, 34]. For instance, Nguyen et al. [6] and Ge et al. [20] analyze interaction logs to assess how following versus ignoring recommendations shifts consumption diversity over time. Anwar et al. [23] simulate different consumption routines to observe how varying levels of exploration can disrupt the reinforcement loop. Ge et al. [20] distinguish various types of behavior on an e-commerce platform when assessing the magnitude of the filter bubble effect.

Preferences The set of interests, tastes, and opinions possessed by the user. It answers *what the user wants to consume*, capturing thematic interests or political stances. Preferences are considered across a significant portion of the sampled literature [43, 23, 24, 19, 28, 21, 7, 35, 45, 38, 46, 22]. To assess the filter bubble, researchers often vary initial user stances; for example, Haim et al. [21] and Ali et al. [43] use personas with opposing political alignments to test if platforms systematically differentiate content delivery. Wang et al. [22] address mitigation by modeling “belief degrees” and using nudging strategies to broaden these preferences toward less-preferred topics through progressively diverse recommendations.

Characteristics The stable, intrinsic traits or attributes that exist independently of specific system interactions (e.g., demographics, socioeconomics, or digital literacy). It establishes *who the user is*, acting as a moderating variable on the filter bubble effect. A limited number of studies specifically isolate user characteristics [47, 40, 48, 21, 7, 49]. Hussein et al. [7] study the influence of age and gender on the filter bubble formation on YouTube through sockpuppet audit, while Bechmann and Nielbo [47] test whether age or education significantly predicts bubble formation in social media news feeds.

Cognitive Mechanisms The psychological mechanisms and biases (e.g., confirmation bias, homophily) that govern how users process information. It dictates *how the user decides what to select*. Cognitive aspects are studied in multiple papers [19, 26, 40, 48, 9, 32, 39]. Geschke et al. [9] and Keizer et al. [32] model individual cognitive filters, such as the “latitude of acceptance,” to theorize how psychological repulsion from opposing views accelerates polarization. Chen [48] explore filter bubble mitigation through the lens of user “self-adaptation” strategies to maintain agency.

Experience The subjective evaluation or psychological state derived during and after the interaction. It captures *how the user perceives the system*, focusing on satisfaction, serendipity, or a sense of control. Experience is isolated in these papers [4, 33, 41, 42, 44]. Mitigation studies frequently target this sub-component; for instance, Nagulendra and Vassileva [41] and Tintarev et al. [42] measure how interactive visualizations increase a user’s perceived understanding and sense of control, while Gao

et al. [4] propose reinforcement learning specifically to optimize long-term user satisfaction, arguing that this is indirectly linked to the diversity of recommendations, and thus mitigates filter bubbles.

User Context The dynamic, situational variables active during interaction, such as temporal, geographic, or device-specific states. It defines *when and where the interaction occurs*. User context is isolated in the following papers [43, 19, 47, 21, 7, 49, 44]. Vannieuwenhuyze et al. [50] isolate geographic context by querying from nineteen different search locations to observe differences in results. On the other hand, Van Damme et al. [44] study the influence of the usage context on mobile platforms, from receiving a notification when inactive, to active consultation of content, on the perception of being in a filter bubble.

4.1.3. Social Context

As an environmental component, the **Social Context** captures the external social dynamics that influence the recommendation flow [51]. It establishes *by whom the user-system interactions are influenced*, defining the broader ecosystem (e.g., peer networks, platform topology, social influence). To resolve potential conceptual overlap, the framework makes a strict distinction: while *User Context* captures an individual’s localized, transient state (e.g., time, device), **Social Context** represents the overarching social structure that acts upon the user and the system [9]. Social context is isolated in the following papers [24, 47, 25, 9, 29, 30, 32, 37, 39]. To assess bubble formation, researchers often manipulate the network structure or the presence of social filters. For instance, Geschke et al. [9] and Iannelli et al. [30] model the social network as a filter in itself, where an agent’s exposure is restricted by the opinions of their immediate peer group. Bechmann and Nielbo [47] identify “sociality”—the number of page likes and friends—as the strongest predictor for being in a filter bubble, outweighing demographic characteristics.

4.2. Information Exchanges

Inspired by systems thinking (e.g., [17]), relationships formalize an exchange of information (e.g., recommendations or behavioral feedback) between the components. We identify two types: **Singular Information Exchanges** and **Repeated Information Exchanges**.

Singular Information Exchange Many papers model only a singular exchange of information between components [24, 47, 48, 29, 7, 32, 33, 35, 36, 37, 41, 45, 42, 50, 39, 52]. For example, Vannieuwenhuyze et al. [50] model a singular information exchange from the **User** → **Recommender System** by means of a search query and geographic location to observe how this user input affects the recommender system output.

Repeated Information Exchange Repeated information exchanges capture longitudinal system evolution, establishing, for example, reinforcement and feedback loops between the user and the system [53, 54]. A substantial proportion of the reviewed papers identify and model such repeated information exchanges [43, 23, 19, 10, 25, 26, 40, 27, 4, 28, 20, 9, 21, 30, 31, 32, 46, 34, 55, 6, 49, 38, 44, 22]. The most common configuration is the closed loop between the **User** and the **Recommender System**; for example, Anwar et al. [23] and Li et al. [34] model how user consumption (User → System) provides the training signals for future recommendations (System → User), creating a spiral of narrowing exposure. Furthermore, Berman and Katona [25] explore a loop between the **User** and the **Social Context**, where a user’s decision to follow peers alters the network structure, which the system then uses to filter subsequent content.

4.3. Observational Components

Observational Components denote the specific location where the filter bubble effect is empirically measured. Observations manifest across various components of the recommendation flow. For instance,

studies frequently measure the diversity or characteristics of the *Algorithm* outputs exposed to the user [55]. Alternatively, observations may target the user directly by measuring *Behavior* patterns, capturing only the items the user actually engages with [23, 49], or by tracking changes in *Preferences* [31]. While many studies isolate a single observational component, others have multiple components; for example, Nguyen et al. [6] measure both *Algorithm* exposure diversity and **User** consumption diversity.

4.4. Impacting Components

Impacting Components are components that are systematically varied or manipulated to observe how they impact the filter bubble formation. For example, researchers have compared how alternative *Algorithms* [36, 38], evaluating different *Interfaces* [26, 33], or altering the underlying *Data* conditions [31] impacts filter bubble formation. Similarly, user-centric components are frequently manipulated to assess their impact on the filter bubble. Studies vary user *Behavior* (e.g., comparing users who adhere to recommendations against those who ignore them [6]), alter pre-existing *Preferences* (e.g., testing different political typologies or seed topics [35, 21]), or manipulate user *Characteristics* by employing diverse socio-demographic archetypes [49].

4.5. Three Archetypes of Filter Bubble Operationalization

To illustrate the analytical value of the conceptual framework, we apply it to three canonical case studies (cf. Figure 1) that exemplify three recurrent archetypes of filter bubble operationalization: 1) *the Algorithmic Exposure Bubble*, 2) *the User-Behavior-Narrowing Bubble*, and 3) *the Preference-Reinforcement Bubble*. Through these case studies and archetypes, we demonstrate how the framework provides a structured vocabulary for categorizing the empirical work, thus enabling more fine-grained evidence synthesis. Importantly, as the final case study will show, the archetypes are not mutually exclusive. Several studies in the coded sample include multiple observations corresponding to different archetypes. The full application of the framework to all coded and validation papers, including the corresponding filter bubble archetypes, is provided in the supplementary material on Zenodo².

Algorithmic Exposure Bubble First, a particularly prominent archetype observes the filter bubble in the output of the **Recommender System**, especially the *Algorithm*. This archetype thus locates the filter bubble before any downstream user effect. The main impacting components are either system-side, most often the *Algorithm*, or user-side, most often the *User Behavior* and *Preferences*. The *Algorithmic Exposure Bubble* is the empirical counterpart to conceptual work that defines the filter bubble in technological terms. It is therefore most closely aligned with Zuiderveen Borgesius et al. [3]’s definition of the filter bubble as a form of “pre-selected personalization” and with Dahlgren [11]’s definition of the “technological filter bubble”, later advanced in our prior work [2].

A canonical example of this archetype is our own prior work, Michiels et al. [55], although this archetype is visible in several studies in our sample [21, 56, 55, 45, 7, 52, 36, 6]. In Michiels et al. [55], we model an information environment consisting of two components: a black-box **Recommender System** and the **User**, with *User Behavior* as the only explicitly modeled sub-component. Further, we model **Repeated Information Exchanges** between the **Recommender System** and the **User**. The filter bubble itself is observed in the **Recommender System**, namely as the topic and political diversity of the recommendations made to a user. Finally, we treat the **Recommender System** as the main impacting component, operationalized through comparisons of two news websites with different recommender systems, and between popularity-based and collaborative filtering-based recommendations.

User-Behavior-Narrowing Bubble A second recurring archetype observes the filter bubble in *User Behavior*, i.e., in what users actually do with the recommendations they receive: what they click, consume, revisit, or repeatedly engage with. This archetype thus moves one step further downstream than the *Algorithmic Exposure Bubble*: the filter bubble is no longer observed at the system-side, but rather in the narrowing of the user’s consumption. Interestingly, the impacting components are

predominantly system-side, with a specific focus on the *Algorithm*. The *User-Behavior-Narrowing Bubble* therefore aligns closely with Pariser’s broader concerns about how personalization changes what users encounter and repeatedly choose, including his worries about overexposure to familiar or attention-grabbing content [1].

A canonical example of this archetype is Anwar et al. [23], although it is similarly visible in several studies in our sample [10, 26, 34, 6, 36, 49, 44]. In Anwar et al. [23], the information environment again consists of two main components: the *Recommender System* and the *User*. Here, the user side is modeled in greater detail through both *Behavior* and *Preferences*. Further, the study models **Repeated Information Exchanges** between the **Recommender System** and the **User**, specifically between the *Algorithm* and the *User Behavior*, with *User Preferences* modeled as part of the user-side structure through which this loop unfolds. In contrast to Michiels et al. [55], Anwar et al. [23] observe the filter bubble in *User Behavior*, operationalizing it through the inter- and intra-user diversity of consumed recommendations. Finally, they treat the *Algorithm* as the main impacting component, both for assessing how recommendation strategies shape the filter bubble and for evaluating mitigation through diversity-oriented interventions.

Preference-Reinforcement Bubble A third frequent archetype observes the filter bubble in *User Preferences*. In this archetype, the filter bubble is observed not as system-side narrowed exposure or narrowed user behavior, but as a reinforcement, stabilization, or gradual reshaping of what the user wants, prefers, or is predisposed to consume. The impacting components are once again primarily system-side, with a focus on the *Algorithm* and *Data*. Importantly, all the studies in our sample that correspond to this archetype model **Repeated Information Exchanges** are consistent with the idea of the filter bubble as a gradual reinforcement of preferences. Conceptually, the *Preference-Reinforcement Bubble* comes closest to Pariser’s original concerns about auto-propaganda and confirmation bias [1], because it operationalizes the filter bubble as shaping the user’s orientation toward information over time. It is therefore also the archetype most closely connected to Bruns [5]’s and Dahlgren [11]’s definitions of the societal filter bubble, as well as to approaches to adjacent concepts such as selective exposure and echo chambers.

A canonical example of this archetype is Gausen et al. [28], although it is similarly visible in several studies in our sample [31, 9, 38, 30, 32, 22, 19]. In Gausen et al. [28], the information environment consists of the *Algorithm*, the *User Preferences*, the *User Behavior*, and the **Social Context**. The study models **Repeated Information Exchanges** between the **Recommender System** and the **User**, as well as between the **User** and the **Social Context**. The *Preference-Reinforcement Bubble* is observed in the *User Preferences*, and the *Algorithm* is considered the main impacting factor: four algorithms with different objectives are evaluated to observe their effect. Gausen et al. [28] also demonstrate that archetypes are not mutually exclusive. In addition to a *Preference-Reinforcement Bubble*, they also evaluate an *Algorithmic Exposure Bubble*.

5. Discussion

The conceptual framework distinguishes the components involved in filter bubble formation and mitigation, the information exchanges between them, the observational components where the bubble is measured, and the impacting components treated as shaping it. In doing so, it reveals differences often left implicit in prior work and provides a structured lens for interpreting the heterogeneous empirical literature on filter bubbles. Here, we focus on three broader implications of this analysis: for evidence synthesis, for the relationship between the filter bubble and the echo chamber, and for how empirical work tends to explain filter bubble formation.

Evidence Synthesis The conceptual framework and three archetypes offer a partial explanation for why evidence synthesis on filter bubbles has been so difficult and why prior empirical work has often produced contrasting findings: Different studies operationalize fundamentally different phenomena

under the same label. As the archetypes showed, some studies locate the filter bubble in the recommender system's output, others in user behavior, and still others in reinforced user preferences. The framework and archetypes make this source of heterogeneity visible and explicit by detailing modeled components, information exchanges, observational components, and impacting components. In doing so, it offers a structured basis for a more precise comparison of studies that might otherwise appear to investigate the same phenomenon, while in fact operationalizing different archetypes of the filter bubble, thereby enabling more meaningful evidence synthesis.

The Echo Chamber and Preference-Reinforcement Bubble The framework and archetypes also make clear that one archetype in particular shares important similarities with the echo chamber and selective exposure: the *preference-reinforcement bubble*. All three concepts concern the reinforcement of users' preferences, tastes, or opinions over time. However, the framework also provides a principled way to distinguish between them. In framework terms, selective exposure and echo chambers are primarily driven by the **User**: it is the user who, because of their *Preferences* and/or *Cognitive Mechanisms*, repeatedly engages with content or peers that reinforce existing views [13]. In contrast, in a *preference-reinforcement bubble*, the main impacting component is the **Recommender System** and its sub-components, even if user-side sub-components are also often presumed to contribute. This distinction matters because empirical studies may observe preference reinforcement and still differ fundamentally in whether they attribute it primarily to algorithmic curation or to user-driven selection. The framework thus makes explicit that these concepts may point to similar outcomes, while differing in the mechanisms through which those outcomes are theorized to arise.

Narrow Focus on the Algorithm Across all three archetypes, the *Algorithm* consistently emerges as the dominant impacting component. This highlights a significant gap in the empirical literature: Real-world environments in which filter bubbles may arise consist of more than algorithmic ranking alone. As our framework demonstrates, a **Recommender System** can also be decomposed into other relevant sub-components: the *Interface*, the *Data*, and the *Stakeholders* who intervene in the recommendation process. However, these are much less frequently treated as having a substantial influence on the filter bubble formation or mitigation. This suggests that the literature often adopts a narrow, algorithm-centered perspective, potentially overlooking how interface design choices, data constraints, and stakeholder interventions shape what users encounter and how they respond. Obtaining a realistic and comprehensive understanding of how filter bubbles may arise in practice requires modeling these subcomponents.

6. Conclusion

This paper set out to clarify how filter bubbles are operationalized in the empirical literature. Based on a grounded theory analysis of 40 studies, we derived an empirically grounded conceptual framework that makes explicit the main components involved in filter bubble formation, the information exchanges between them, the locations where filter bubbles are observed, and the components treated as impacting their formation or mitigation. Applying this framework, we identified three distinct archetypes of filter bubble operationalization: *the Algorithmic Exposure Bubble*, *the User-Behavior-Narrowing Bubble*, and *the Preference-Reinforcement Bubble*.

Taken together, the framework and archetypes show that empirical studies do not all investigate the same filter bubble. Rather, they often operationalize the phenomenon in fundamentally different ways. This helps explain why the literature has produced contrasting findings and why evidence synthesis has remained so difficult. By making these differences explicit, our framework provides a structured vocabulary for categorizing and comparing empirical studies of filter bubbles more precisely.

Beyond this, the framework also helps situate the filter bubble in relation to adjacent concepts, most notably the echo chamber, and highlights potential theoretical and methodological blind spots in the current literature, including a strong and often overly narrow focus on the algorithm. We therefore see

this work as a foundation for future synthesis and empirical research: it can support more meaningful comparison within shared archetypes, help identify underexplored operationalizations, and contribute to a more rigorous understanding of how filter bubbles may arise in recommender systems.

Declaration on Generative AI

During the preparation of this work, the authors used Grammarly for “Grammar and spelling check”, Google Gemini for “Grammar and spelling check” and “Improve writing style”, ChatGPT for “Improve writing style” and “Paraphrase and reword”. After using these tool(s)/service(s), the author(s) reviewed and edited the content as needed and take(s) full responsibility for the publication’s content.

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A. Supplementary Material

The supplementary material is available on Zenodo at <https://doi.org/10.5281/zenodo.20036303>. It includes the full coded set, descriptive statistics of the coded papers, documentation of the data collection procedures for both the coding and validation sets, the validation set, and the application of the framework to both the coded and validation papers.