Wirtschaftsinformatik 2023 Proceedings Wirtschaftsinformatik

10-9-2023

Unraveling Information-Limiting Environments: An Empirical Review of Individual, Social, and Technological Filters in Social Media

Kian Schmalenbach
FAU Erlangen-Nürnberg, Germany, kian.schmalenbach@fau.de

Eva Gengler
FAU Erlangen-Nürnberg, Germany, eva.gengler@fau.de

Sebastian Schötteler
FAU Erlangen-Nürnberg, Germany, sebastian.schoetteler@th-nuernberg.de

Sven Laumer
FAU Erlangen-Nürnberg, Germany, sven.laumer@fau.de

Unraveling Information-Limiting Environments: An Empirical Review of Individual, Social, and Technological Filters in Social Media
Research Paper

Kian Schmalenbach[1], Eva Gengler[1], Sebastian Schötteler[1,2], and Sven Laumer[1]

[1] FAU Erlangen-Nürnberg, Institut für Wirtschaftsinformatik, Nuremberg, Germany
{kian.schmalenbach,eva.gengler,sven.laumer}@fau.de
[2] Technische Hochschule Nürnberg, Fakultät Informatik, Nuremberg, Germany
{sebastian.schoetteler@th-nuernberg.de}

Abstract. Social media platforms offer a convenient way for people to interact and exchange information. However, there are sustained concerns that filter bubbles and echo chambers create information-limiting environments (ILEs) for their users. Despite a well-developed conceptual understanding, the empirical evidence regarding the causes and supporting conditions of these ILEs remains inconclusive. This paper addresses this gap by applying the triple-filter-bubble model developed by Geschke et al. (2019) to analyze empirical literature on the individual, social, and technological causes of ILEs. While we identify some factors that increase the probability of ILEs under certain conditions, our findings do not suffice to thoroughly validate conceptual models that explain why ILEs emerge. Therefore, we call for future research to investigate the causes of ILEs with higher external validity to develop a more comprehensive understanding of this phenomenon.

Keywords: Echo Chambers, Filter Bubbles, Information-Limiting Environments, Social Media, Triple-Filter-Bubble Model

1 Introduction

Social media platforms play a crucial role in our society, facilitating global connection, interaction, and information sharing. However, they also pose significant risks, such as misinformation spread, public opinion manipulation, and polarization (Abouzeid et al. 2019, Kitchens et al. 2020, Vicario et al. 2016). The Club of Rome has even identified the propagation of misinformation as the most urgent challenge of our time (Dixson-Decleve et al. 2022). The term "filter bubble," coined by Eli Pariser (2011), highlights the dangers associated with social media. Personalization and filtering algorithms create this phenomenon by presenting users with content that aligns with their past behavior and inferred personality traits. This approach discourages users from encountering information that challenges their beliefs, leading to a limited understanding of available information (Helberger et al. 2018). Consequently, users may be exposed mainly to content that reinforces their existing opinions, resulting in polarization and the formation of "echo chambers" where like-minded individuals continuously reinforce each other's beliefs (Sunstein 2002). These phenomena collectively give rise to an *information-limiting* *environment (ILE)* that significantly restricts the quantity, diversity, and perspectives of information accessible to social media users (Kitchens et al. 2020).

Understanding the causes of ILEs in social media platforms is complex due to factors such as rapid content growth driven by network effects (Van Alstyne & Brynjolfsson 2005), personalized mechanisms shaping available information (Eg et al. 2023), and social phenomena like homophily and group polarization (Bakshy et al. 2015). The intricate nature of these factors hinders both theoretical and empirical analysis of specific antecedents leading to ILE emergence. To address this challenge, Geschke et al. (2019) propose a framework that categorizes ILE antecedents into three types: individual, social, and technological filters. Individual filters encompass cognitive processes influencing users' information consumption behavior, social filters involve network structure and dynamics contributing to ILEs, and technological filters refer to algorithmic causes of ILEs in social media (Geschke et al. 2019).

While such conceptual frameworks are useful for classifying ILE antecedents, their explanatory power is often limited due to the absence of empirical validation. The complex nature of ILEs, involving sociotechnical interactions and human psychology, necessitates empirical investigation with real individuals instead of relying solely on data obtained from computer simulations (Geschke et al. 2019). In this vein, a recent comprehensive review of empirical research on ILEs by Terren & Borge (2021) highlights the inconclusive nature of empirical findings on antecedents causing ILE emergence, as they appear to depend on context-specific factors such as data collection methods. These observations indicate a lack of a comprehensive overview of empirical evidence on the diverse causes of ILE emergence in the existing literature. To address this gap, we conduct a structured literature review to systematically analyze and synthesize existing empirical findings related to individual users, social contexts, and technological factors associated with ILE emergence. Therefore, we formulate the following research question:

RQ: *What is the current empirical evidence regarding the role of individual users, social context, and technological factors in the emergence of ILEs in social media?*

In addressing this research question, our objective is to provide a comprehensive and well-structured overview of the existing empirical research on ILE antecedents. Through this analysis, we will assess the adequacy of the aggregated empirical literature for validating conceptual frameworks that explain the emergence of ILEs. If the current empirical evidence is sufficient for validation, our paper will contribute by offering researchers a valuable and comprehensive overview of empirically supported data for explaining ILE emergence. Alternatively, if the literature lacks the necessary empirical support, our study will still make a significant contribution by systematically highlighting this limitation and making the case for future research aimed at empirically deriving and testing the concepts proposed in conceptual papers.

This paper is structured as follows. Section 2 introduces the relationship between ILEs and social media platforms, and the theoretical background of the three ILE antecedents. Section 3 describes the methodology. Section 4 presents the findings, and Section 5 concludes the paper by discussing the results.

2 Theoretical Background

2.1 Information-Limiting Environments in Social Media

Social media can be defined as "a group of Internet-based applications that build on the ideological and technological foundations of Web 2.0, and that allow the creation and exchange of user-generated content" (Kaplan & Haenlein 2010). Common social media types are social networking sites (e.g., Facebook), content communities (e.g., YouTube), and (micro)blogs (e.g., Twitter) (Kaplan & Haenlein 2010). Social media enable users to access diverse user-generated information from a large information universe (Boyd & Ellison 2007). However, the emergence of echo chambers and filter bubbles on social media can limit this diversity (Kitchens et al. 2020). Filter bubbles and echo chambers are often used as synonyms. However, they are intertwined yet ultimately distinct concepts. A filter bubble is "the outcome of different processes of information search, perception, selection, and remembering the sum of which causes individual users to receive from the universe of available information only a tailored selection that fits their pre-existing attitudes" (Geschke et al. 2019). An echo chamber is "a social phenomenon where the filter bubbles of interacting individuals strongly overlap" (Geschke et al. 2019).

Put differently, filter bubbles are the individual information spaces social media users maintain, whereas echo chambers refer to the overlap of individual information spaces. For instance, Reddit relies on its users' characteristics, such as locations or interests, to provide them with relevant subreddits (e.g., subreddits about local sports clubs or political orientations). Further, Reddit provides a personalized timeline by which its users are regularly updated with popular posts from their subreddits. Thus, the information users see on Reddit is influenced by their subreddits followed, leading to the emergence of filter bubbles (Linder et al. 2018). Further, Reddit enables its users to discuss in subreddits dedicated to particular topics. Thus, subreddits can be echo chambers in which mainly like-minded individuals with overlapping filter bubbles interact. This phenomenon is further reinforced by the fact that interacting in specific subreddits is sometimes reserved for users following these subreddits. In general, filter bubbles and echo chambers can emerge on various social media platforms next to Reddit, including Facebook (Bechmann & Nielbo 2018) and Twitter (Bozdag et al. 2014).

Despite the conceptual differences between filter bubbles and echo chambers, the commonality between these concepts is that they are ILEs: "We propose the concept of information-limiting environments as encapsulating the primary concerns regarding echo chambers and filter bubbles—namely, that social network homophily and algorithmic filtering constrain the information sources that individuals choose to consume, shielding them from opinion-challenging information and encouraging them to adopt more extreme viewpoints" (Kitchens et al. 2020). We adopt this definition for our paper.

2.2 Individual, Social, and Technological Filters in Social Media

Social media platforms provide valuable opportunities for participatory deliberation in democratic societies, enabling users to access, create, and evaluate vast amounts of content (Bernstein et al. 2021). However, due to the overwhelming volume of information available on the internet, the need for information limitation and filtering has arisen (Bruckner et al. 2022). These techniques aim to enhance relevance by curating and prioritizing content based on individual interests and needs (Eg et al. 2023). Nonetheless, the emergence of ILEs poses a significant threat to the democratic process of participation. By constraining the quantity, diversity, and bias of information users encounter, ILEs can undermine fundamental rights such as freedom of speech, expression, and opinion formation (Bernstein et al. 2021, Committee 2011). Moreover, ILEs can introduce biases into users' political and factual perspectives on socially relevant issues, contributing to societal polarization through the reinforcement of echo chambers (Arora et al. 2022). Hence, it is crucial for users, platform operators, and policymakers to comprehend the conditions under which ILEs arise and the reasons behind their emergence.

While the existence of network effects and social homophily in both offline and online networks is well-known (Bakshy et al. 2015), the complexity of the phenomenon is heightened by algorithmic personalized filtering at the individual level and the ease with which users, including bots, can contribute to or influence information flow within a network. In this vein, Geschke et al. (2019) proposed the *triple-filter-bubble model* as a theoretical framework to categorize the filtering processes that give rise to ILEs. This model provides a conceptual understanding of why ILEs, as defined by Kitchens et al. (2020), emerge by identifying three key antecedents. Firstly, *individual filters* encompass cognitive biases at the individual level that influence how users search for, process, and remember information. Secondly, *social filters* pertain to the influence of social connections and interactions in forming close relationships among user subgroups who share similar characteristics or beliefs, which can affect the flow of information through a network. Lastly, *technological filters* are algorithmic in nature and arise from monetary incentives or technological constraints, leading algorithms to filter information based on their perceived relevance in the recommendations provided to users.

Recent reviews have revealed inconclusive empirical findings regarding respective ILE antecedents, emphasizing the need for further investigations into the causes of ILE emergence (Arora et al. 2022, Terren & Borge 2021). Therefore, we conduct a structured literature review of empirical papers addressing ILE antecedents, utilizing the triple-filter-bubble model as a theoretical framework. We argue that this model is well-suited for examining the emergence of ILEs from an Information Systems perspective, as it allows for the exploration of socio-technical interaction processes while explicitly differentiating between individual and group-level phenomena. In doing so, our objective is to provide a comprehensive understanding of the factors contributing to ILE development, thereby evaluating the adequacy of the existing empirical literature in validating conceptual frameworks that elucidate the emergence of ILEs.

3 Method

The goal of this paper is twofold. The first goal is to quantitatively and qualitatively review the literature on the antecedents of filter bubbles and echo chambers on social media. The second is to derive future research directions. Both goals comply with literature review research (Webster & Watson 2002). Thus, we adapted the literature review research methodology from vom Brocke et al. (2009). Consequently, our method encompasses four steps. In the first step, we defined this paper's scope and conceptualized our topic within this scope to establish a concept matrix (Webster & Watson 2002). As discussed so far, we set our scope on filter bubble and echo chamber antecedents on social media. Within this scope, we used the framework from Geschke et al. (2019) to conceptualize such antecedents into individual, social, and technological antecedents. We used this conceptualization as it has the potential to provide nuanced insights that exceed single empirical domains and resolve possible conflicting findings. Hence, our resulting matrix enabled categorizing literature findings based on the underlying type of filter bubble or echo chamber antecedent.

In the second step, we populated our concept matrix with relevant literature findings using a systematic literature search approach. Here, we initially defined four inclusion criteria. First, we only included peer-reviewed papers to increase the validity of our findings inferred from the papers. Second, we only included papers published no earlier than 2000 because the first social media papers emerged around this time (Mazlish 2000). Third, in line with our goal to evaluate the adequacy of the existing empirical literature in establishing and validating conceptual frameworks explaining ILE emergence, we specifically focused on empirical papers that examined individual, social, or technological filter bubble or echo chamber antecedents on social media. Fourth, we only included English papers to ensure a sufficient understanding of the papers. As social media is a global and dynamic phenomenon (Kaplan & Haenlein 2010), we included papers irrespective of their underlying publication country or outlet type (i.e., journals or conferences).

After defining the inclusion criteria, we selected three multidisciplinary databases and a list of search terms to derive papers from these databases. We selected Scopus, Web of Science, and EBSCOhost as the databases due to their high level of reproducibility and coverage (Gusenbauer & Haddaway 2019). To query these databases, we selected the central search terms "social media", "echo chamber", and "filter bubble". This list was augmented by synonymous and further relevant terms, namely "social network", "social software", "selective exposure", and "content diversity". For greater coverage, the plural forms of the search terms were also included in the search term list (e.g., "echo chambers"). Our list of search terms is largely congruent with the terms and wordings used in related literature reviews (e.g., Wehner et al. 2017, Terren & Borge 2021) and empirical papers (e.g., Huellmann & Sensmeier 2022). A preliminary study revealed that our scope was highly interdisciplinary. Thus, rather than relying on a predefined set of literature sources—such as the Senior Scholar's List of Premier Journals (AIS 2023)—we applied the list of search terms to query relevant papers from all sources indexed in all three databases. This query revealed 804 papers whose titles, abstracts, or keywords contained both a social media-related and an ILE-related search term.

Next, we scrutinized each paper to infer whether it met the inclusion criteria. Doing so reduced the initial list of 804 to a list of 52 papers. Then, two raters conducted an interrater check to cross-validate whether the papers in this list fulfilled all inclusion criteria. 48 papers received inclusion votes from both raters, while the remaining 4 only received inclusion votes from one of the raters. We used the rater information to calculate Gwet's interrater reliability coefficient (Gwet 2014). Here, we achieved a value of 0.92, indicating substantial validity (Gwet 2014). After internal discussion, we decided to include 1 of the conflicting 4 papers, whereas the residual 3 papers were excluded. Hence, our final list consisted of 49 papers. The most relevant literature sources were the "Social Media and Society" source with 5 papers, followed by the "PLOS ONE" and "ACM Web Conference" sources with 4 papers each, followed by the "Computers in Human Behavior" and "Social Science Computing Review" sources with 3 papers each.

In the last two steps, we established the quantitative and qualitative literature review and inferred directions for future research. For the quantitative literature review, we classified the papers' underlying findings based on publication year, outlet type, antecedent type, addressed social media platform, and social media type (note that a paper can reveal more than one finding). For the qualitative literature review, we used a thematic analysis approach (Braun & Clarke 2006). First, one of the authors categorized each finding into the concept matrix based on its type of addressed filter bubble or echo chamber antecedent (i.e., individual, social, or technological). The author then abstracted conceptually similar findings within each category into higher-level, conceptually distinct antecedents. Overall, this led to 11 higher-level antecedents. To increase methodological rigor, the coding approach was subsequently cross-validated by another author. Lastly, we synthesized the findings belonging to each distinct antecedent as well as how these findings conflict or corroborate with the findings from the other antecedents. To infer directions for future research, we studied the concept matrix as well as the quantitative and qualitative literature reviews.

4 Results

The final set of 49 papers formed the basis for the description of the results in the following sections. Firstly, we present the results of our quantitative analysis. Secondly, we present the results of our qualitative analysis, focusing on the three types of ILE antecedents.

4.1 Quantitative Analysis

Table 1 provides a distribution of the paper findings published per year and overarching antecedent type. Although our sample included papers from various years, all papers were published between 2013 and 2023.

Table 1. Distribution of literature findings from the 41 journal and 8 conference articles reviewed

Year*	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**	**2021**	**2022**	**2023**	**Total**
Individual	1	2		6		1	4	6	1	4	1	26
Social	1	2	1	6	2	5	3	2	1	1	1	25
Technological		1	1					2	1	3	1	9
Total	2	5	2	12	2	6	7	10	3	8	3	60

** The annual distribution concerns publication years and does not account for the duration of the research and publication process.*

Individual antecedent findings were inferred from 26 papers. Moreover, social antecedent findings were inferred from 25 papers. Lastly, technological antecedent findings were inferred from nine papers. Regarding the empirical methods used in the papers, we observed that data analyses from social media platforms were utilized in 22, surveys in 11, experiments in 11, field studies in five, and focus group research in one of the papers. One paper used a combination of data analysis and a survey. Notably, less than a quarter of the papers applied experiments despite the method's potential higher suitability in testing assumptions on the impact of specific antecedents on ILEs in comparison with the other methods (Gregor & Hovorka 2011). The platforms examined in the studies included Twitter in 17, Facebook in 14, YouTube in three, Reddit in two, Instagram in one, and TikTok in one case. Five articles relied on other websites (e.g., experimental mockups). Further 12 articles conducted their research independently of any particular platform. Note that some papers addressed more than one social media platform. The unequal representation of platforms may indicate potential gaps in understanding ILEs in social media types beyond text-based ones, such as Instagram and TikTok.

Table 2 presents a concept matrix that summarizes the number of findings per antecedent type and social media platform type. This table provides an overview of the distribution of findings and will be discussed in more detail in subsequent sections. Noticeably, the number of findings in Table 2 may exceed the number of findings in Table 1, as each antecedent type finding can be further operationalized into multiple findings based on the specific antecedents and social media platforms addressed.

Table 2. Concept matrix summarizing the literature findings based on antecedent and platform

	Social Networking		**Microblogs**	**Content Communities**			**General**
Antecedent	Facebook	Instagram	Twitter	Reddit	TikTok	YouTube	
Individual	**19**	**2**	**9**	**2**	**0**	**1**	**18**
Demographics	2	1	1	0	0	0	3
Personality Traits	3	0	1	0	0	0	1
Cognitive Factors	4	0	1	0	0	0	4
Political Attitude	5	1	3	1	0	0	8
Usage Behavior	5	0	3	1	0	1	2
Social	**8**	**0**	**13**	**0**	**0**	**2**	**5**
Network Structure	1	0	4	0	0	0	3
Subgroup Formation	1	0	5	0	0	2	0
Interaction Patterns	6	0	4	0	0	0	2
Technological	**1**	**0**	**1**	**0**	**2**	**3**	**4**
Algorithmic Interaction	0	0	0	0	1	1	1
Network Influence	0	0	1	0	1	0	2
Content Characteristics	1	0	0	0	0	2	1

4.2 Individual Antecedents of ILEs

As defined by Geschke et al. (2019), *individual filters* are antecedents that pertain to the cognitive or behavioral traits of individual users and contribute to ILEs. Among the papers in our sample, 26 provided evidence regarding the impact of user traits or behaviors on information-filtering processes, which we have further classified as follows.

Demographics. In our sample, six studies examined the relationship between demographic characteristics and the emergence of ILEs. While evidence suggests that certain demographics, such as females, young people, and those with a low education level, may be more likely to encounter ILEs, none of these findings were definitively confirmed. Specifically, three studies (Chan et al. 2022, Parmelee & Roman 2020, Sindermann et al. 2020) found a possible association between female gender and ILEs. One study (An et al. 2013) found a correlation between liberal males and ILE emergence, and another study (Parmelee & Roman 2020) indicated that Caucasian race and young age may be antecedents for ILEs. Two studies (Boulianne & Koc-Michalska 2022, Chan et al. 2022) suggested that a low education level may increase the probability of ILEs.

Personality Traits. Our review examined four studies investigating the association between the "Big Five" personality traits and ILEs. However, conclusive evidence for any specific personality trait was not found. The first study (Bessi 2016) indicated a negative impact of agreeableness, conscientiousness, and extraversion on ILEs, while emotional stability and openness had a positive impact. The second study (Boulianne & Koc-Michalska 2022) reported a positive impact of conscientiousness and a negative impact of extraversion on ILEs. The third study (Sindermann et al. 2020) found a negative effect of emotional stability and openness on ILEs. Lastly, the fourth study (An et al. 2013) did not observe any effects related to personality traits.

Cognitive Factors. Nine studies in our sample investigated the impact of cognitive processes on ILEs. Consistent evidence emerged for the positive impact of confirmation bias (An et al. 2014, Brugnoli et al. 2019, Sülflow et al. 2019) and negative emotions (Del Vicario et al. 2016, Jeong et al. 2019) on ILE emergence. Gullibility (Mosleh et al. 2021), perceived information overload (Auxier & Vitak 2019), and general trust in media (Chan et al. 2022) increased the likelihood of ILEs, while cognitive reflection (Mosleh et al. 2021) and anxiety (Auxier & Vitak 2019) were associated with a decrease. Additionally, accuracy-based motivation for seeking information did not have an effect, while a defense-oriented motivation had a positive impact (Winter et al. 2016).

Political Attitude. In our sample, 14 studies investigated the relationship between political views and ILEs. Overall, it was found that political knowledge increased the likelihood of encountering an ILE (An et al. 2014), while the impact of political interest varied, with some studies showing a negative effect (Boulianne & Koc-Michalska 2022, Sindermann et al. 2020) and others finding no effect (Ohme & Mothes 2020). Regarding political opinion, conflicting evidence was found for conservatism, with two studies reporting a positive impact (Parmelee & Roman 2020, Sindermann et al. 2020) and two others indicating a negative impact (An et al. 2014, Shin 2020). Moreover, partisanship in general was identified as a significant antecedent of ILEs by three studies (Auxier & Vitak 2019, Chan et al. 2022, Robertson et al. 2023), while one study found no effect (Boulianne & Koc-Michalska 2022), and another study suggested a platform-dependent positive effect (Kitchens et al. 2020). Consistent evidence supported a positive effect of polarization (Beam et al. 2018, Reiter et al. 2022), but only one study found a positive effect of ideological orientation (Shin 2020), while three others did not observe this effect (Cargnino & Neubaum 2022, Chan et al. 2022, Parmelee & Roman 2020). Finally, political congruence was identified as an antecedent of ILEs by one study (Vraga 2016), while another study did not find a respective effect (Cargnino & Neubaum 2022).

Usage Behavior. Eight studies explored the influence of usage behavior on ILEs. Early interaction with new content (Bessi et al. 2016) and active re-sharing behavior (An et al. 2014, Bozdag et al. 2014) were identified as significant predictors of ILEs. However, the number of posts a user generates did not correlate with ILE emergence (An et al. 2013). Moreover, the impact of usage frequency on ILEs varied across platforms, with frequent Twitter use showing a partial association with increased risk, while frequent use of Facebook and Reddit appeared to decrease the risk (Chan et al. 2022, Cinelli et al. 2020, Kitchens et al. 2020, Vaccari et al. 2016). Considering the partially contradictory platform-specific findings, usage frequency may not reliably predict ILEs overall.

4.3 Social Antecedents of ILEs

As per Geschke et al. (2019), ILEs are caused by *social filters* formed by homogeneous network structures, where individuals connect with others who share similar characteristics or beliefs. In this section, we present our findings on the social factors contributing to ILEs on social media, based on an analysis of the 25 relevant papers from our sample.

Network Structure. Eight studies in our sample explored the characteristics of the network structure and their influence on ILEs. Network diversity (Wohn & Bowe 2016) and network stability (Yang et al. 2021) were found to have a negative effect on ILEs. The presence of gatekeepers, such as popular users or opinionated journalists, was identified as a catalyst for ILEs in three studies focused on the Twitter network (Garimella et al. 2018, Hong & Kim 2016, Vergeer 2015). Additionally, a platform-independent study revealed the role of strategic content dissemination agents in creating a skewed perception of majority opinion among readers, contributing to ILEs (Kim 2019). The impact of network size on ILE emergence varied, with one study suggesting that large networks may support ILEs (Yang et al. 2021), while two others found no significant effect (An et al. 2013, Reiter et al. 2022).

Subgroup Formation. Eight studies identified the formation of homophilic subgroups as a significant contributor to ILEs at the social level. Proximity in terms of demographics (Monti et al. 2023), geography (Bastos et al. 2018, Kaiser & Rauchfleisch 2020), and ideology (Boutyline & Willer 2017, Bright 2018) demonstrated a positive impact on ILE emergence. Moreover, homophilic offline networks (Vaccari et al. 2016) and right-leaning ideological subgroups (Boutyline & Willer 2017) were particularly associated with ILEs, especially on Twitter. Conflicting narratives also predicted ILEs on Facebook and YouTube (Bessi 2016). Finally, research indicated that multilingual users held central positions in the information network, while monolingual users were more likely to encounter ILEs (Bodrunova et al. 2018, Kaiser & Rauchfleisch 2020).

Interaction Patterns. Twelve studies investigated the impact of social interaction motivation or behavior on ILEs. Regarding motivation, approval seeking correlated with ILE emergence in two studies (Awobamise & Jarrar 2019, Wohn & Bowe 2016). Similarly, the receipt of endorsements or likes was found to foster ILEs in two studies (Anspach 2017, Awobamise & Jarrar 2019), although two other studies did not observe this effect (An et al. 2013, Ohme & Mothes 2020). One study also revealed that an increase in negative comments on posts heightened the risk of ILEs (Del Vicario et al. 2016). In terms of behavior, one study found a positive influence of homophilic peer influence on ILEs (Brugnoli et al. 2019), while another study found no impact of peer-induced mainstreaming or polarization on ILEs (Shore et al. 2018). Additionally, two studies focused on Twitter reported a negative association between cascading information dissemination among non-connected users (Liang 2018) and the frequency of inter-group exchange (Yang et al. 2021), and ILE emergence. However, direct interaction with seed users demonstrated a positive impact on ILEs, both on Facebook and Twitter (Bozdag et al. 2014, Shore et al. 2018). Finally, one study found that users who extensively share posts are more likely to encounter ILEs on both Facebook and Twitter (An et al. 2014).

4.4 Technological Antecedents of ILEs

According to Geschke et al. (2019), *technological filters* refer to algorithms that yield a selective subset of the information available on a platform. Given our focus on empirical studies utilizing actual social media platforms, we did not expect to discover purely technical explanations or remedies for these phenomena. Instead, our analysis of the nine relevant studies from our sample highlights factors that unintentionally contribute to algorithmic conditions on social media platforms, potentially fostering ILEs.

Algorithmic Interaction. Three studies investigated the unintended influence of users on algorithmically induced ILEs, primarily focusing on video platforms such as YouTube and TikTok. These studies revealed that interaction duration and content liking significantly trigger TikTok's recommender algorithm to promote ILE emergence (Boeker & Urman 2022), while the user's location on YouTube does not contribute to algorithmically induced the emergence of ILEs (Kaiser & Rauchfleisch 2020). Furthermore, one study demonstrated that the user's consumption preferences greatly influence the extent of ILEs caused by content-based recommender algorithms (Han et al. 2022).

Network Influence. Four studies have examined how network characteristics contribute to ILEs. A cross-platform study revealed that social media users are more susceptible to being trapped in ILEs compared to users of other websites (Nikolov et al. 2015). Homophilic network structures were found to influence algorithms in filtering information (Ferrara et al. 2022), and popular content creators on Twitter were identified as contributors to algorithmically induced ILEs (Bozdag et al. 2014). However, one study focused on TikTok found that following a larger number of users increases diversity in recommended videos, thereby mitigating ILEs (Boeker & Urman 2022).

Content Characteristics. Four studies revealed that the content itself can inadvertently contribute to algorithmically induced ILEs. Content with a strong political bias, particularly favoring right-wing ideologies, was found to foster ILEs on Facebook and YouTube (Ali et al. 2021, Kaiser & Rauchfleisch 2020, Röchert et al. 2020). Additionally, content with negative sentiment was observed to increase ILE occurrence, albeit the strength of this effect decreases over time (Ludwig et al. 2023).

4.5 Literature Synthesis

Social media can contribute to ILEs via filter bubbles and echo chambers (Kitchens et al. 2020), although empirical evidence on their causes remains inconclusive. In our literature review utilizing the triple-filter-bubble model (Geschke et al. 2019), we analyzed 49 empirical papers investigating individual, social, and technological factors contributing to the emergence of ILEs. Our findings reveal that specific antecedents of ILEs often yield inconclusive or contradictory results. Concerning individual antecedents of ILEs, the impact of political attitude shows conflicting findings, with political knowledge increasing ILE risk (An et al. 2014) while political interest decreasing it (e.g., Sindermann et al. 2020) and conservative beliefs showing ambiguous effects (e.g., Parmelee & Roman 2020, Shin 2020)). Similarly, most demographic factors and none of the big five personality traits show a clear influence (e.g., Bessi 2016). Regarding social antecedents, there is a bias towards Facebook and Twitter in the literature, and contradictory findings are observed between these platforms. For instance, network size significantly affects ILEs on Twitter (Yang et al. 2021) but not on Facebook (An et al. 2013), and homophilic peer influence creates ILEs on Facebook (Brugnoli et al. 2019) but not on Twitter (Shore et al. 2018). Finally, technological antecedents are overall underrepresented in the literature, with a focus on specific platforms like YouTube (Kaiser & Rauchfleisch 2020, Röchert et al. 2020) and TikTok (Boeker & Urman 2022), limiting generalizability due to different algorithms used by each platform.

Concerning research methodology, the majority of studies (22 out of 49) adopted a data-driven approach using social media datasets. Hence, inconsistent results were observed across platforms and contexts, making it difficult to develop a unified theory of ILE emergence without knowledge of the missing moderating factors. Furthermore, many combinations of antecedents and platforms are still understudied or unexplored, as can be seen in Table 2. Therefore, our findings indicate that, despite evidence regarding some factors that contribute to the emergence of ILEs, the limited and ambiguous nature of the evidence hampers the development of a sound explanatory theory based on cause-effect relationships. As a result, we are unable to provide sufficient empirical validation for findings derived from conceptual models such as the triple-filter-bubble model. Instead, we conclude our study by emphasizing the need for future research to (i) systematically classify potential antecedents of ILEs, (ii) collect context-independent empirical data, and (iii) integrate these findings into a unified causal theory of ILE emergence.

5 Discussion

5.1 Theoretical and Practical Implications

Concerning theory, our interdisciplinary literature review reveals a lack of generalizability of empirical evidence on ILEs in social media, with studies primarily correlational, focusing on individual events (e.g., Bodrunova et al. 2018) or specific social media (e.g., Beam et al. 2018, Röchert et al. 2020). This limited scope hinders reconciling conflicting or inconclusive evidence and identifying explanatory factors. Moreover, heavy reliance on data from social media APIs raises concerns about data representativeness. Hence, future research should include more counterfactual or experimental studies to validate reproducible direct or moderated effects on ILEs. We also encourage IS researchers to intensify efforts in theorizing the causes of ILEs in social media. Our results align with past reviews in displaying that the subject area is highly context-sensitive, promoting conflicting results (e.g., Arora et al. 2022, Terren & Borge 2021). However, in contrast to these reviews, our study is the first to explicitly investigate antecedents of ILEs.

Concerning practice, we emphasize the significance of digital literacy for social media users. Given the lack of conclusive evidence regarding the factors contributing to the occurrence of ILEs in social media, we suggest exploring the potential of social media literacy as a promising avenue (Cho et al. 2022). Secondly, we urge policy-makers to monitor the emergence of ILEs in social media and other platforms. The proliferation of data-driven applications, including advanced AI-based tools like ChatGPT, raises concerns about the dissemination of online misinformation and fake news, which pose threats to democratic societies (Bernstein et al. 2021, Helberger 2019). Hence, it is crucial to have clearer evidence of the conditions that lead to ILEs in online networks, particularly in social media, in order to uphold free and informed online discourse.

5.2 Limitations and Future Research Opportunities

While the triple-filter-bubble model provides valuable insights into ILE antecedents, our review is constrained by the three factors encompassed by this model, potentially excluding other causes of ILEs (Geschke et al. 2019). Future research should expand the theoretical framework to incorporate additional potential factors contributing to ILEs. Additionally, our search procedure, relying on selected multidisciplinary databases and predefined search terms, may have representative rather than exhaustive coverage, possibly overlooking relevant papers. To address this limitation, future studies could employ more comprehensive search methods. Lastly, our review exclusively focused on empirical papers, potentially neglecting evidence from alternative approaches such as agent-based modeling or design-oriented studies. Future research could broaden the selection criteria to include articles utilizing these methodologies.

6 Acknowledgements

This research was funded by the German Federal Ministry of Education and Research (BMBF) through grants 01IS17045 Software Campus 2.0 (FAU Erlangen-Nürnberg).

References

Abouzeid, A., Granmo, O., Webersik, C. & Goodwin, M. (2019), Causality-Based Social Media Analysis for Normal Users Credibility Assessment in a Political Crisis, *in* Niemi V. & Tyutina T., eds, 'Proceedings of the 24th Conference of Open Innovations Association', IEEE Computer Society, pp. 3–14.

AIS (2023), 'Senior Scholar's List of Premier Journals'.
URL: *https://aisnet.org/page/SeniorScholarListofPremierJournals*

Ali, M., Sapiezynski, P., Korolova, A., Mislove, A. & Rieke, A. (2021), Ad Delivery Algorithms: The Hidden Arbiters of Political Messaging, *in* 'Proceedings of the 14th ACM International Conference on Web Search and Data Mining', Association for Computing Machinery, pp. 13–21.

An, J., Quercia, D. & Crowcroft, J. (2013), Fragmented Social Media: A Look into Selective Exposure to Political News, *in* 'Proceedings of the 2013 ACM Web Conference', Association for Computing Machinery, pp. 51–52.

An, J., Quercia, D. & Crowcroft, J. (2014), Partisan Sharing: Facebook Evidence and Societal Consequences, *in* 'Proceedings of the 2014 ACM Conference on Online Social Networks', Association for Computing Machinery, pp. 13–23.

Anspach, N. (2017), 'The New Personal Influence: How Our Facebook Friends Influence the News We Read', *Political Communication* **34**(4), 590–606.

Arora, S., Singh, G., Chakraborty, A. & Maity, M. (2022), 'Polarization and Social Media: A Systematic Review and Research Agenda', *Technological Forecasting and Social Change* **183**(1), 121942.

Auxier, B. & Vitak, J. (2019), 'Factors Motivating Customization and Echo Chamber Creation Within Digital News Environments', *Social Media and Society* **5**(2), 1–13.

Awobamise, A. & Jarrar, Y. (2019), 'Exploring the Impact of Social and Source Cues on News Selection', *Plaridel* **16**(1), 141–160.

Bakshy, E., Messing, S. & Adamic, L. (2015), 'Exposure to Ideologically Diverse News and Opinion on Facebook', *Science* **348**(6239), 1130–1132.

Bastos, M., Mercea, D. & Baronchelli, A. (2018), 'The Geographic Embedding of Online Echo Chambers: Evidence from the Brexit Campaign', *PLOS ONE* **13**(11), 1–16.

Beam, M., Hutchens, M. & Hmielowski, J. (2018), 'Facebook News and (De)polarization: Reinforcing Spirals in the 2016 US Election', *Information Communication and Society* **21**(7), 940–958.

Bechmann, A. & Nielbo, K. (2018), 'Are We Exposed to the Same "News" in the News Feed?', *Digital Journalism* **6**(8), 990–1002.

Bernstein, A., de Vreese, C., Helberger, N., Schulz, W., Zweig, K., Baden, C., Beam, M., Hauer, M., Heitz, L., Jürgens, P., Katzenbach, C., Kille, B., Klimkiewicz, B., Loosen, W., Moeller, J., Radanovic, G., Shani, G., Tintarev, N., Tolmeijer, S., van Atteveldt, W., Vrijenhoek, S. & Zueger, T. (2021), 'Diversity in News Recommendation', *Dagstuhl Manifestos* **9**(1), 43–61.

Bessi, A. (2016), 'Personality Traits and Echo Chambers on Facebook', *Computers in Human Behavior* **65**(1), 319–324.

Bessi, A., Zollo, F., Del Vicario, M., Puliga, M., Scala, A., Caldarelli, G., Uzzi, B. & Quattrociocchi, W. (2016), 'Users Polarization on Facebook and Youtube', *PLOS ONE* **11**(8), 1–24.

Bodrunova, S., Smoliarova, A., Blekanov, I., Zhuravleva, N. & Danilova, Y. (2018), 'A Global Public Sphere of Compassion? #jesuischarlie and #jenesuispascharlie on Twitter and Their Language Boundaries', *The Monitoring of Public Opinion Economic& Social Changes* **1**(143), 267–295.

Boeker, M. & Urman, A. (2022), An Empirical Investigation of Personalization Factors on Tiktok, *in* 'Proceedings of the 2022 ACM Web Conference', Association for Computing Machinery, Inc, pp. 2298–2309.

Boulianne, S. & Koc-Michalska, K. (2022), 'The Role of Personality in Political Talk and Like-Minded Discussion', *International Journal of Press/Politics* **27**(1), 285–310.

Boutyline, A. & Willer, R. (2017), 'The Social Structure of Political Echo Chambers: Variation in Ideological Homophily in Online Networks', *Political Psychology* **38**(3), 551–569.

Boyd, D. & Ellison, N. (2007), 'Social Network Sites: Definition, History, and Scholarship', *Journal of Computer-Mediated Communication* **13**(1), 210–230.

Bozdag, E., Gao, Q., Houben, G.-J. & Warnier, M. (2014), 'Does Offline Political Segregation Affect the Filter Bubble? An Empirical Analysis of Information Diversity for Dutch and Turkish Twitter Users', *Computers in Human Behavior* **41**(1), 405–415.

Braun, V. & Clarke, V. (2006), 'Using Thematic Analysis in Psychology', *Qualitative Research in Psychology* **3**(1), 77–101.

Bright, J. (2018), 'Explaining the Emergence of Political Fragmentation on Social Media: The Role of Ideology and Extremism', *Journal of Computer-Mediated Communication* **23**(1), 17–33.

Bruckner, M., Grüning, M., Lindenmayr, M. & Schmalenbach, K. (2022), 'Mind the Gap: A Theory Development Approach for Explaining the Divergence of Human Information Processing Capacity and Information Amount'.

Brugnoli, E., Cinelli, M., Quattrociocchi, W. & Scala, A. (2019), 'Recursive Patterns in Online Echo Chambers', *Scientific Reports* **9**(1), 1–18.

Cargnino, M. & Neubaum, G. (2022), 'Is It Better to Strike a Balance? How Exposure to Congruent and Incongruent Opinion Climates on Social Networking Sites Impacts Users' Processing and Selection of Information', *New Media and Society* **0**(0), 1–19.

Chan, C., Zhao, M. & Lee, P. (2022), 'Determinants of Escape from Echo Chambers: The Predictive Power of Political Orientation, Social Media Use, and Demographics', *Global Media and China* **0**(0), 1–19.

Cho, H., Cannon, J., Lopez, R. & Li, W. (2022), 'Social Media Literacy: A Conceptual Framework', *New Media and Society* **0**(0), 1–20.

Cinelli, M., Brugnoli, E., Lucia Schmidt, A., Zollo, F., Quattrociocchi, W. & Scala, A. (2020), 'Selective Exposure Shapes the Facebook News Diet', *PLOS ONE* **15**(3), 1–17.

Committee, U. N. H. R. (2011), 'International Covenant on Civil and Political Rights'. **URL:** *https://www.refworld.org/docid/4ed34b562.html*

Del Vicario, M., Vivaldo, G., Bessi, A., Zollo, F., Scala, A., Caldarelli, G. & Quattrociocchi, W. (2016), 'Echo Chambers: Emotional Contagion and Group Polarization on Facebook', *Scientific Reports* **6**(1), 1–12.

Dixson-Decleve, S., Gaffney, O., Ghosh, J., Randers, J., Rockstrom, J. & Stoknes, P. (2022), *Earth for All: A Survival Guide for Humanity*, 1 edn, New Society Publishers.

Eg, R., Demirkol, O. & Tennfjord, M. (2023), 'A Scoping Review of Personalized User Experiences on Social Media: The Interplay Between Algorithms and Human Factors', *Computers in Human Behavior Reports* **9**(1), 1–17.

Ferrara, A., Espin-Noboa, L., Karimi, F. & Wagner, C. (2022), Link Recommendations: Their Impact on Network Structure and Minorities, *in* 'Proceedings of the 14th ACM Web Science Conference', Association for Computing Machinery, pp. 228–238.

Garimella, K., De Francisci Morales, G., Gionis, A. & Mathioudakis, M. (2018), Political Discourse on Social Media: Echo Chambers, Gatekeepers, and the Price of Bipartisanship, *in* 'Proceedings of the 2018 ACM Web Conference', Association for Computing Machinery, pp. 913–922.

Geschke, D., Lorenz, J. & Holtz, P. (2019), 'The Triple-Filter Bubble: Using Agent-Based Modelling to Test a Meta-Theoretical Framework for the Emergence of Filter Bubbles and Echo Chambers', *British Journal of Social Psychology* **58**(1), 129–149.

Gregor, S. & Hovorka, D. (2011), Causality: The Elephant in the Room in Information Systems Epistemology, *in* 'Proceedings of the 19th European Conference on Information Systems', Association for Information Systems, pp. 1–12.

Gusenbauer, M. & Haddaway, N. (2019), 'Which Academic Search Systems Are Suitable for Systematic Reviews or Meta-Analyses? Evaluating Retrieval Qualities of Google Scholar, Pubmed, and 26 Other Resources', *Research Synthesis Methods* **11**(2), 181–217.

Gwet, K. (2014), *Handbook of Inter-Rater Reliability: The Definitive Guide to Measuring the Extent of Agreement Among Raters*, 4 edn, Advanced Analytics.

Han, H., Wang, C., Zhao, Y., Shu, M., Wang, W. & Min, Y. (2022), 'SSLE: A Framework for Evaluating the "Filter Bubble" Effect on the News Aggregator and Recommenders', *World Wide Web* **25**(3), 1169–1195.

Helberger, N. (2019), 'On the Democratic Role of News Recommenders', *Digital Journalism* **7**(8), 993–1012.

Helberger, N., Karppinen, K. & D'Acunto, L. (2018), 'Exposure Diversity as a Design Principle for Recommender Systems', *Information, Communication & Society* **21**(2), 191–207.

Hong, S. & Kim, S. (2016), 'Political Polarization on Twitter: Implications for the Use of Social Media in Digital Governments', *Government Information Quarterly* **33**(4), 777–782.

Huellmann, J. & Sensmeier, L. (2022), No Filter Bubbles? Evidence from an Online Experiment on the News Diversity of Personalizing News Aggregators, *in* 'Proceedings of the 2022 Pacific Asia Conference on Information Systems', Association for Information Systems, pp. 1–17.

Jeong, M., Zo, H., Lee, C. & Ceran, Y. (2019), 'Feeling Displeasure from Online Social Media Postings: A Study Using Cognitive Dissonance Theory', *Computers in Human Behavior* **97**(1), 231–240.

Kaiser, J. & Rauchfleisch, A. (2020), 'Birds of a Feather Get Recommended Together: Algorithmic Homophily in Youtube's Channel Recommendations in the United States and Germany', *Social Media and Society* **6**(4), 1–15.

Kaplan, A. & Haenlein, M. (2010), ‘Users of the World, Unite! The Challenges and Opportunities of Social Media’, *Business Horizons* **53**(1), 59–68.

Kim, S. (2019), ‘Directionality of Information Flow and Echoes Without Chambers’, *PLOS ONE* **14**(5), 1–22.

Kitchens, B., Johnson, S. & Gray, P. (2020), ‘Understanding Echo Chambers and Filter Bubbles: The Impact of Social Media on Diversification and Partisan Shifts in News Consumption’, *MIS Quarterly: Management Information Systems* **44**(4), 1619–1650.

Liang, H. (2018), ‘Broadcast Versus Viral Spreading: The Structure of Diffusion Cascades and Selective Sharing on Social Media’, *Journal of Communication* **68**(3), 525–546.

Linder, R., Stacy, A., Lupfer, N., Kerne, A. & Ragan, E. (2018), Pop the Feed Filter Bubble: Making Reddit Social Media a VR Cityscape, *in* ‘Proceedings of the 2018 IEEE Conference on Virtual Reality and 3D User Interfaces’, IEEE Computer Society, pp. 619–620.

Ludwig, K., Grote, A., Iana, A., Alam, M., Paulheim, H., Sack, H., Weinhardt, C. & Müller, P. (2023), ‘Divided by the Algorithm? The (Limited) Effects of Content- and Sentiment-Based News Recommendation on Affective, Ideological, and Perceived Polarization’, *Social Science Computer Review* **0**(0), 1–23.

Mazlish, B. (2000), ‘Invisible Ties: From Patronage to Networks’, *Theory, Culture and Society* **17**(1), 1–19.

Monti, C., D’Ignazi, J., Starnini, M. & Morales, G. (2023), Evidence of Demographic Rather Than Ideological Segregation in News Discussion on Reddit, *in* ‘Proceedings of the 2023 ACM Web Conference’, Association for Computing Machinery, pp. 1–10.

Mosleh, M., Pennycook, G., Arechar, A. & Rand, D. (2021), ‘Cognitive Reflection Correlates with Behavior on Twitter’, *Nature Communications* **12**(1), 1–10.

Nikolov, D., Oliveira, D., Flammini, A. & Menczer, F. (2015), ‘Measuring Online Social Bubbles’, *PeerJ Computer Science* **2015**(12), 1–14.

Ohme, J. & Mothes, C. (2020), ‘What Affects First- and Second-Level Selective Exposure to Journalistic News? A Social Media Online Experiment’, *Journalism Studies* **21**(9), 1220–1242.

Pariser, E. (2011), *The Filter Bubble: How the New Personalized Web Is Changing What We Read and How We Think*, 1 edn, Penguin.

Parmelee, J. & Roman, N. (2020), ‘Insta-Echoes: Selective Exposure and Selective Avoidance on Instagram’, *Telematics and Informatics* **52**(1), 1–10.

Reiter, F., Heiss, R. & Matthes, J. (2022), ‘Explaining Attitude-Consistent Exposure on Social Network Sites: The Role of Ideology, Political Involvement, and Network Characteristics’, *Social Science Computer Review* **0**(0), 1–20.

Robertson, R., Green, J., Ruck, D., Ognyanova, K., Wilson, C. & Lazer, D. (2023), ‘Users Choose to Engage with More Partisan News Than They Are Exposed to on Google Search’, *Nature* **618**(1), 342–348.

Röchert, D., Weitzel, M. & Ross, B. (2020), The Homogeneity of Right-Wing Populist and Radical Content in Youtube Recommendations, *in* ‘Proceedings of the 2020 International Conference on Social Media and Society’, Association for Computing Machinery, pp. 245–254.

Shin, J. (2020), ‘How Do Partisans Consume News on Social Media? A Comparison of Self-Reports with Digital Trace Measures Among Twitter Users’, *Social Media and Society* **6**(4), 1–12.

Shore, J., Baek, J. & Dellarocas, C. (2018), 'Network Structure and Patterns of Information Diversity on Twitter', *MIS Quarterly: Management Information Systems* **42**(3), 849–872.

Sindermann, C., Elhai, J., Moshagen, M. & Montag, C. (2020), 'Age, Gender, Personality, Ideological Attitudes and Individual Differences in a Person's News Spectrum: How Many and Who Might Be Prone to "Filter Bubbles" and "Echo Chambers" Online?', *Heliyon* **6**(1), 1–10.

Sunstein, C. (2002), 'The Law of Group Polarization', *Journal of Political Philosophy* **10**(2), 40.

Sülflow, M., Schäfer, S. & Winter, S. (2019), 'Selective Attention in the News Feed: An Eye-Tracking Study on the Perception and Selection of Political News Posts on Facebook', *New Media and Society* **21**(1), 168–190.

Terren, L. & Borge, R. (2021), 'Echo Chambers on Social Media: A Systematic Review of the Literature', *Review of Communication Research* **9**(1), 1–39.

Vaccari, C., Valeriani, A., Barberá, P., Jost, J., Nagler, J. & Tucker, J. (2016), 'Of Echo Chambers and Contrarian Clubs: Exposure to Political Disagreement Among German and Italian Users of Twitter', *Social Media and Society* **2**(3), 1–24.

Van Alstyne, M. & Brynjolfsson, E. (2005), 'Global Village or Cyber-Balkans? Modeling and Measuring the Integration of Electronic Communities', *Management Science* **51**(6), 851–868.

Vergeer, M. (2015), 'Peers and Sources as Social Capital in the Production of News: Online Social Networks as Communities of Journalists', *Social Science Computer Review* **33**(3), 277–297.

Vicario, M., Bessi, A., Zollo, F., Petroni, F., Scala, A., Caldarelli, G., Stanley, H. & Quattrociocchi, W. (2016), 'The Spreading of Misinformation Online', *Proceedings of the National Academy of Sciences of the United States of America* **113**(3), 554–559.

vom Brocke, J., Simons, A., Niehaves, B., Riemer, K., Plattfaut, R. & Cleven, A. (2009), Reconstructing the Giant: On the Importance of Rigour in Documenting the Literature Search Process, *in* 'Proceedings of the 17th European Conference on Information Systems', Association for Information Systems, pp. 1–14.

Vraga, E. (2016), 'Party Differences in Political Content on Social Media', *Online Information Review* **40**(5), 595–609.

Webster, J. & Watson, R. (2002), 'Guest Editorial: Analyzing the Past to Prepare for the Future: Writing a Literature Review', *MIS Quarterly* **26**(2), xiii–xxiii.

Wehner, B., Ritter, C. & Leist, S. (2017), 'Enterprise Social Networks: A Literature Review and Research Agenda', *Computer Networks* **114**(1), 125–142.

Winter, S., Metzger, M. & Flanagin, A. (2016), 'Selective Use of News Cues: A Multiple-Motive Perspective on Information Selection in Social Media Environments', *Journal of Communication* **66**(4), 669–693.

Wohn, D. & Bowe, B. (2016), 'Micro Agenda Setters: The Effect of Social Media on Young Adults' Exposure to and Attitude Toward News', *Social Media and Society* **2**(1), 1–12.

Yang, A., Choi, I., Abeliuk, A. & Saffer, A. (2021), 'The Influence of Interdependence in Networked Publics Spheres: How Community-Level Interactions Affect the Evolution of Topics in Online Discourse', *Journal of Computer-Mediated Communication* **26**(3), 148–166.