Media use in algorithmic environments

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Abstract |

This article explores the characteristics and implications of media use in *algorithmic environments*—defined as technical channels or platforms that personalise media content through algorithmic systems and deliver it to users in an individualised way. It examines the roles these systems play in media use and their broader social significance. The focus then shifts to the interaction between users and algorithmic environments, including users' knowledge that algorithms exist (*algorithmic awareness*), their perceptions of how algorithms operate (*algorithmic sensemaking*), and the importance of developing skills to navigate these systems (*algorithmic literacy*). The article concludes by discussing potential effects of media use in algorithmic environments on information and opinion formation, and briefly addresses related methodological challenges.

Keywords |

Algorithms, filtering, opinion-forming, personalisation, social media platforms

1. Introduction

Media use has always been shaped by prioritisation and recommendations from others. The placement and layout of an article in a newspaper signal its importance. A smiling red star in a TV guide suggests which film is worth watching, while radio charts highlight the latest music hits. Likewise, advertising posters in city centres or tips from friends and family influence not only what media we choose to engage with, but also how we perceive and interpret it. In recent years, with the advance of digitalisation, a new type of curator has emerged alongside these journalistic, strategic, and social actors: *algorithms* (Thorson & Wells, 2016; Wallace, 2018). Today, a considerable portion of media consumption—whether for information or entertainment—takes place within so-called *algorithmic environments* (e.g., ARD/ZDF-Forschungskommission, 2024; Newman et al., 2024). Audio streaming services such as Spotify create personalised playlists for us, video platforms such as YouTube automatically suggest thematically related content after a video finishes, and social media apps like Instagram decide which photos or videos appear first when we open the app. These processes of classification, prioritisation, and filtering are driven by mathematical models that consider a range of signals and data—such as which songs a user frequently listens to, which videos they have liked, the preferences of similar users, or whether a company has paid to have its content prominently featured (see e.g. DeVito, 2017; Lischka & Stöcker, 2017; Ricci et al., 2015; Schwartz & Mahnke, 2021). Thus, algorithms are playing an increasingly important role in shaping which media content we engage with, how informed or entertained we feel by it, and what content influences our opinions.

Against this backdrop, this article aims to examine the characteristics of media use in algorithmic environments and explore its implications for users. The focus is specifically on how algorithmic systems affect 'normal' users. As such, the article does not address the use of algorithms in contexts such as comment moderation by community managers, the detection of misinformation by platform operators, or the support or automation of journalistic content creation (see, for example, Haim & Graefe, 2018). It also excludes considerations of how media providers are adapting to the growing role of algorithmic environments in the distribution of their content (see, for example, Hadida et al., 2021; Zamith, 2019).

The article begins by defining the terms "algorithm" and "algorithmic (media) environments," followed by a discussion of the roles algorithmic systems play in media use and the broader social significance of using media content in such environments. Building on this, the article analyses various dynamics that emerge from the growing reliance on algorithmic systems. Central questions include whether media users are even aware of how algorithms shape their media experience (*algorithmic awareness*), how their (perceived) understanding of these systems influences their engagement with content (*algorithmic sensemaking*), and the importance of developing broader skills for navigating algorithmic environments (*algorithmic literacy*). The article concludes by briefly examining the potential implications of algorithmic media use and the methodological challenges involved in studying it.

2. Foundations

2.1 Definitions: Algorithms and algorithmic media environments

A popular T-shirt and coffee mug slogan in online shops humorously defines an *algorithm* as a "word used by programmers when they do not want to explain what they did." This joke reflects a broader reality: many media users have only a vague idea of what an algorithm is. According to a representative survey conducted by the Bertelsmann Stiftung in January 2022, 17% of respondents had never even heard the term "algorithm," 21% said they had little understanding of how algorithms work, and 44% claimed to have at least a general idea (Overdiek & Petersen, 2022, p. 17; see also Chung & Wihbey, 2024). Given these figures—and the fact that the term is used differently across various disciplines (Gillespie, 2016; Heise, 2016)—this article will begin by clarifying what is meant by "algorithms" and "algorithmic (media) environments."

At its most basic, algorithms can be understood as step-by-step procedures for solving problems (Herzog, 2021, p. 199), with the aim of generating a specific output—such as an engaging newsfeed or suitable film recommendations—from a given input (e.g., user data or observed behaviour) (see also Diakopoulos, 2015; Gillespie, 2016; Heise, 2016). A common way to explain how algorithms work is by using the analogy of a *recipe* (see, e.g., Gillespie, 2016; Willson, 2017). A recipe has a clear goal—for example, preparing a vegetable curry. It lists the necessary ingredients—such as coconut milk, broccoli, and sweet potatoes—and outlines a precise sequence of steps, including how finely to chop the vegetables, the order in which to add them to the pot, and the appropriate heat level for simmering. In this analogy, the ingredients represent the input, the finished curry is the output, and the cooking instructions are the algorithm.

Unlike cooking recipes, however, algorithms in information technology require precise instructions and definitions. A vague direction like 'a blob of maple syrup' must be translated into a specific quantity to ensure machine readability and reproducibility. But whether in the kitchen or in digital environments, one thing remains the same: "Algorithms make things happen" (Willson, 2017, p. 140), producing a result based on a finite set of instructions designed by their creators.

Although public discourse often refers to *the* Netflix algorithm or *the* Instagram algorithm, this phrasing oversimplifies reality (Kitchin, 2017; Mosseri, 2021; Seaver, 2019; Silva et al., 2022). In practice, platforms like these operate using a multitude of algorithms—or, more accurately, algorithmic systems that can be defined as "intricate, dynamic arrangements of people and code" (Seaver, 2019, p. 419). From a communication science perspective, it is important to reflect this complexity in our language. As such, academic discussions typically refer not to 'the algorithms,' but to algorithmic media (e.g. Bucher, 2020), to media that employ algorithmic recommendation systems (Schmidt et al., 2018, p. 522), or to the use of such systems by information intermediaries[1] (e.g. Stark et al., 2021). As indicated by the title, this article uses the term *algorithmic (media) environments* to refer to all technical channels or platforms that automatically personalise media content using algorithmic systems. This means delivering content to users in an individualised manner based on explicitly and implicitly generated preference profiles (see similarly Schweiger et al., 2019; Silva et al., 2022).

This definition requires further explanation, especially regarding the concept of *personalisation*. Thurman and Schifferes (2012) define personalisation as a "form of user-to-system interactivity that uses a set of technological features to adapt the content, delivery, and arrangement of a communication to individual users' explicitly registered and/or implicitly determined preferences" (p. 776). Based on this and similar conceptualisations (see, e.g., Bozdag, 2013; Thorson & Wells, 2016; Zuiderveen Borgesius et al., 2016), a distinction can be made between implicit and explicit personalisation in algorithmic media environments. *Implicit personalisation* occurs when the system infers user preferences from observable behaviour and other signals and uses this information to prioritise and filter content. In algorithmic media environments, this might include the types of content users engage with, the device or location from which they access it, or the intensity of their interactions with other users in their network. Combined with additional metadata—such as content type, publication time, or popularity cues like the number of views—a computational decision is made about which content to display. In contrast, *explicit personalisation* (sometimes referred to as personal curation, see, e.g., Merten, 2021) refers to users actively and deliberately selecting the content they want to see—or avoid—by setting preferences themselves. Explicit personalisation occurs, for example, when a user subscribes to an account on a social media platform or uses features like 'Not interested' to reduce the visibility of similar posts in the future. In algorithmic media environments, both implicit and explicit personalisation work together—though implicit personalisation generally

[1] Strictly speaking, intermediaries are services that make third-party content accessible (Schweiger et al., 2019, p. 12) and produce little to no content of their own—such as search engines or social media platforms. This means that not all of the channels or platforms discussed in this article (e.g., streaming services that also produce their own content) can be accurately described as intermediaries.

dominates (see also Schweiger et al., 2019, pp. 10-11). Because acts of explicit personalisation merely *supplement* the content selection process, users do not retain full control over what is shown or how it is ranked. This underscores that algorithmic systems operating in these environments are not static, but dynamic, context-dependent, and continuously evolving (Kitchin, 2017, p. 21).

The exact functioning of automated personalisation—specifically, which input parameters are considered and how they are weighted—remains largely speculative for most algorithmic media systems, as such details are typically kept vague or entirely undisclosed and treated as proprietary business secrets (see, e.g., Mosseri, 2021; Netflix Help Center, n.d.). As a result, algorithmic systems are often referred to as *black boxes* (Diakopoulos, 2015; Hargittai et al., 2020; Heise, 2016), making them difficult or even impossible to analyse in a scientifically rigorous way. Nevertheless, certain methods can offer insight into how these systems function. These include analysing publicly available platform documents (e.g., patent filings, see DeVito, 2017), applying reverse engineering techniques (Diakopoulos, 2015; Thorson et al., 2021), or conducting experiments that manipulate presumed input variables and observe the resulting outputs—such as agent-based testing approaches (Haim, 2020). These strategies can help identify which factors most strongly influence algorithmic outcomes.

Drawing on an analysis of publicly available Facebook documents—including blog posts, patent applications, and SEC filings—DeVito (2017) sought to uncover the algorithmic values underlying the Facebook News Feed. They describe these values as a set of criteria "used to make decisions about the inclusion and exclusion of material and which aspects of said material to present in an algorithmically driven news feed" (p. 754). In total, they identified nine such algorithmic values, with the most influential being: (a) *friend relationship*, (b) *explicitly expressed user interests*, and (c) *prior user engagement* related to rating, discussing, and sharing content. In a methodologically similar analysis focused on Netflix, Gaw (2022) found that implicitly inferred user preferences—such as which titles users watched and for how long, or what they searched for—play a central role in automated personalisation. The behaviour of 'taste dopplegangers' (users with similar viewing habits) also strongly influences recommendations. While explicit personalisation indicators, such as user ratings, are considered, they are generally less influential. One reason is their often performative nature: users may rate critically acclaimed or 'important' films and series highly, even if they actually prefer watching reality shows or baking competitions.

A review of how major algorithmic platforms explain their ranking and prioritisation processes in their help sections reveals a consistent emphasis on *personal relevance* and *positive user experiences*. For example, Facebook refers to making recommendations "that are relevant and valuable to each person who sees them" (Facebook Help Centre, n.d.), TikTok aims to show users "the most interesting and relevant videos" (TikTok Help Centre, n.d.), and YouTube promotes helping users discover "more of the videos you love" (YouTube, n.d.). The following section examines the tasks performed by algorithmic systems and outlines the functions that automated personalisation fulfils for both platform operators and media users.

2.2 Functions: What algorithms do in the context of media use

Algorithmic systems perform a wide range of tasks (see Diakopoulos, 2015; Just & Latzer, 2017). For example, they are used to classify and organise content behind the scenes based on specific characteristics (*classification algorithms*), and to identify relationships between pieces of content, thereby determining their similarity (*association algorithms*). However, in algorithmic media environments, *filtering and prioritisation algorithms* are most noticeable to users.[2] Filtering algorithms determine which content is selected for display from the vast pool available on a platform, while prioritisation algorithms rank this content in a defined order, often based on inferred user relevance or recency. Through these processes of selection and ranking, algorithmic systems assume classic gatekeeping roles (Bozdag, 2013; Hagen et al., 2017; Soffer, 2021; Thorson & Wells, 2016; Wallace, 2018), thereby exerting substantial influence on the flow of information in society.

In the context of media uses and effects, filtering and prioritisation processes—commonly referred to as *recommendation algorithms* due to their core function—are particularly important. This section therefore focuses on how such systems operate, as they constitute the core of algorithmic media environments. The goal of recommendation systems is to continually analyse which content users might be interested in—either next or in the current moment—and to deliver or display relevant content accordingly (Bozdag, 2013; Burke, 2007; Ricci et al., 2015).

[2] Of course, filtering and prioritisation algorithms also rely on the classification of content and associations between items (see also Diakopoulos, 2015, p. 402). However, making an analytical distinction between these functions remains useful for clarifying the primary tasks performed by algorithmic systems.

A range of filtering techniques are used to achieve this, with the literature commonly distinguishing between three basic types (see also Schmidt et al., 2018):

- *Content-based filtering techniques* recommend content to users that is similar to what they have previously consumed or rated positively. Similarity is determined based on defined content attributes—for example, in the case of films, genre, director, cast, or even the moral stance of the protagonists (Gaw, 2022).
- *Collaborative filtering techniques* generate recommendations by comparing and correlating users' viewing and rating profiles. The underlying assumption is that users with similar preferences for certain content will likely respond similarly to other content. For example, if a platform wants to determine whether to recommend a new film to person X, collaborative filtering considers how users with similar past behaviours and preferences responded to that film.
- *Context-based filtering techniques* consider contextual factors such as time, location, or the device in use when generating recommendations. For instance, users might receive different suggestions in the morning than in the evening, or see different content on their smartphone compared to their laptop at home. Depending on data availability, additional factors—such as current weather conditions, recent searches, or the user's social setting—can also influence the recommendations.

When considering the functions of recommendation algorithms, it is important to distinguish between the perspectives of users and platform operators. For users, algorithmic recommendations serve a primarily functional purpose: they help manage the overwhelming volume of information characteristic of online environments. Personalisation according to users' interests and preferences also meets their (often implicit) desire to engage with content that is personally entertaining or relevant. While platform operators often highlight this user benefit in public communications, recommendation algorithms are ultimately optimised to serve the platforms' organisational goals (Ricci et al., 2015; Silva et al., 2022). These goals typically include increasing user satisfaction and time spent on the platform, strengthening user loyalty, and—above all—maximising revenue, both through audience retention and advertising. For profit-driven companies such as social media platforms and streaming services, the core objective of algorithmic curation is therefore the generation of (advertising) revenue. Normative goals such as diversity, balance, or information quality generally play little to no role.

2.3 Relevance: Media use in algorithmic environments

As mentioned in the introduction and throughout this article, several algorithmic media environments and platforms now play a particularly important role in how people consume media. While the prominence of individual services continues to shift, there has been a clear trend in recent years toward media use increasingly shaped by automated personalisation.

In Germany, for instance, the ARD/ZDF Media Study reports that 68% of internet use in 2024 was dedicated to media-related activities. These include (1) the use of video streaming services such as Netflix and Amazon Prime, (2) music streaming via platforms like Spotify or YouTube Music, and (3) reading digital articles (ARD/ZDF-Forschungskommission, 2024). This development mirrors international trends, where the use of music and video streaming services, as well as the growing role of news aggregators, continues to rise (e.g., Duarte, 2025; Newman et al., 2024; Ofcom, 2024). When social media platforms are included—many of which now prominently feature curated content from traditional media outlets (e.g., from TV broadcasters or magazines) as well as content creators—the relevance of media use within algorithmic environments becomes even more evident. In Germany, 60% of the population use social media platforms at least occasionally, engaging with its diverse functionalities (Müller, 2024, p. 2). Similar usage levels are observed in other countries such as Australia, the United States, and the United Kingdom (acma, 2024; Gottfried, 2024; Ofcom, 2024). It can therefore be assumed that a substantial share of online media consumption occurs within algorithmic environments—particularly among younger users (Gottfried, 2024; Müller, 2024; Ofcom, 2024).

The question of how strongly media use is shaped by automated personalisation is of particular societal relevance in the context of news use and access to political information (see also Schweiger et al., 2019). The importance of algorithm-based pathways to news is clearly illustrated by the *Reuters Institute Digital News Report*, which offers representative data on news usage among internet users aged 18 and older in 47 countries (Newman et al., 2024). For the 2024 survey year, the findings show that 62% of respondents accessed news via search engines, news aggregators, or social media platforms. While search engines are equally relevant across age groups, social media play a particularly important role among 18- to 24-year-olds. When looking specifically at active news use on social media—meaning the search for, reading, watching, sharing, or discussing of news (Behre et al., 2024, p. 31)—Facebook emerges as the most frequently used platform across countries, with 24% using it for news. However, notable differences appear across age groups. In Germany, Instagram is by far the most important social media news source among 18- to 24-year-olds: 27% regularly use it to stay informed, followed by YouTube (24%) and TikTok (13%). By contrast, only 7% in this age group turn to Facebook for news (Behre et al., 2024, pp. 31–33). The implications of this 'new form of external control' (Geiß et al., 2018, p. 503) in the realm of information use will be addressed in Section 4.1. First, however, the next section examines whether media users are even aware of how algorithmic systems shape their media experience.

3. Constellations

3.1 Algorithmic Awareness

As shown, a large share of media use today occurs within algorithmic environments. But to what extent are users even aware that the content they see is automatically personalised? This most basic level of *algorithmic awareness* (Oeldorf-Hirsch & Neubaum, 2023, p. 682) forms the foundation for subsequent meaning-making processes (Chapter 3.2) and the development of more advanced competencies (Chapter 3.3). However, the concept itself is not consistently defined in the literature. Some authors describe it narrowly as the awareness "that a dynamic system is in place that can personalise and customize the information that a user sees or hears" (Hargittai et al., 2020, p. 771). Others take a broader view, conceptualising algorithmic awareness as the extent to which people hold accurate beliefs about how algorithms function in specific media environments and how this, in turn, shapes "how users consume and experience media content" (Zarouali et al., 2021, p. 2). In some cases, the term *algorithmic knowledge* is used to describe this more comprehensive understanding (e.g., Cotter & Reisdorf, 2020; Dogruel et al., 2021). Following Dogruel and colleagues (2021, p. 5), this article adopts a narrower definition: algorithmic awareness is understood as the recognition that algorithms exist and are being used—without implying detailed knowledge of how they operate.

Earlier qualitative studies, particularly in the context of Facebook, focused on whether users were aware that not all available posts are shown to them (Eslami et al., 2016; Powers, 2017; Rader & Gray, 2015). These studies found that user awareness of such filtering was generally limited. However, making broad generalisations about users' algorithmic awareness remains challenging for several reasons: a) platforms and their underlying algorithmic systems are constantly evolving, and the transparency with which they communicate about these systems also fluctuates; b) self-reported knowledge about algorithms has generally increased in recent years (Overdiek & Petersen, 2022); and c) awareness differs across platforms. Factors such as the aggressiveness or openness of a platform's algorithmic operations (Siles & Meléndez-Morán, 2021), the intensity and duration of users' engagement (Cotter & Reisdorf, 2020), and the extent to which their experience contradicts expectations (Swart, 2021) all influence how consciously users perceive algorithmic curation. Still, even a basic awareness can give rise to what Bucher (2017) terms an "algorithmic imaginary,"—that is, the emergence of naïve or informal media theories about how these systems operate on specific platforms.

3.2 Algorithmic Sensemaking

Precisely because users often lack detailed knowledge of how algorithms function across platforms, a wide range of assumptions about their workings has emerged. These naïve media theories (Naab, 2013)—a specific form of *folk theories* well-known in social psychology—refer to the informal beliefs users develop to explain how, in our case, personalisation in algorithmic media environments operates. They encompass all user-generated assumptions about the parameters and mechanisms by which content is selected and prioritised (see, e.g., Dogruel, 2021b; Eslami et al., 2016; Ytre-Arne & Moe, 2021).

From a communication science perspective, examining these sense-making processes is valuable not only because they reveal users' actual knowledge (see also Oeldorf-Hirsch & Neubaum, 2023, p. 686), but also because inaccurate or incomplete ideas can meaningfully influence behaviour. Research shows that users' personal theories about how algorithms work affect which content they choose to engage with—or avoid—and shape their expectations of platforms (for an overview, see Cotter, 2022). Much like scientific theories, naïve media theories are subject to testing. For example, if a user believes that increased interaction with a Facebook account will lead to seeing more content from that account (personal engagement theory, Eslami et al., 2016), they may 'test' this assumption by changing their behaviour and observing how their newsfeed responds.

Research has identified a wide range of naïve media theories about algorithmic systems, varying in both their level of abstraction and their focus. Some refer to algorithms in online environments more generally (Dogruel, 2021b), while others focus on specific platforms such as Facebook (Eslami et al., 2016), Spotify (Siles et al., 2020), or TikTok (Karizat et al., 2021). Despite these differences, there are notable overlaps—for example, many users adopt theories based on content popularity ("What is displayed is what is generally popular"), the behaviour of similar users ("What is displayed is what people like who are similar to me"), or their own interaction patterns ("What is displayed is what I frequently use, click on, or rate"). As with scientific theories, naïve media theories are formed either inductively—through personal experience and observation within the platform—or deductively, based on external sources such as media reports about algorithmic systems or the shared beliefs of other users (see also DeVito et al., 2018).

Users often put their (perceived) knowledge of algorithmic systems into practice by actively attempting to 'train' them—either through explicit personalisation features or through strategic patterns of behaviour (Karizat et al., 2021; Siles et al., 2020; Siles et al., 2024). For example, Siles and colleagues (2020) describe how Spotify users deliberately like songs, follow artists, or repeatedly listen to the same albums to signal their preferences to the algorithm. On TikTok—arguably one of the most algorithmically curated platforms—such training practices are considered essential by users (Karizat et al., 2021; Siles et al., 2024). Only through regular liking or targeted searches for preferred content can users begin to 'tame' the For You page. As interviewees noted, TikTok only becomes truly enjoyable once the algorithm has been successfully trained and the app begins to respond in the desired way (Siles et al., 2024, p. 5710). The perceived success of such algorithm training can, in turn, reshape users' naïve media theories, influencing how they understand and explain algorithmic functioning. Among those hoping to succeed as content creators in algorithmic media environments, a growing ecosystem of self-proclaimed algorithm experts has emerged—offering and selling theories about how to boost visibility and reach (Bishop, 2020).

Perceptions of algorithmic systems are closely linked to specific attitudes, which can be placed along a spectrum ranging from *algorithmic aversion* to *algorithmic appreciation* (Oeldorf-Hirsch & Neubaum, 2023, p. 684). These attitudes include general evaluations of the usefulness or quality of algorithmic recommendations, as well as more platform- or situation-specific preferences. Users often react negatively to noticeable changes in algorithmic systems, a sentiment reflected in hashtags like #RIPTwitter or campaigns such as "Make Instagram Instagram Again" (Gollmer, 2022). Ultimately, these attitudes and the associated meaning-making processes are also tied to users' algorithmic literacy, which is becoming increasingly important for navigating algorithmic media environments in a self-determined and informed way.

3.3 Algorithmic Literacy

While communication scholars agree that a solid understanding of algorithmic systems and the ability to navigate algorithmic media environments with confidence are essential for today's users, there have been relatively few efforts to comprehensively define and structure the concept of *algorithmic literacy* (see Dogruel, 2021a; Oeldorf-Hirsch & Neubaum, 2023). A promising and broadly applicable conceptualisation is offered by Dogruel (2021a; Dogruel et al., 2021), who identifies four dimensions based on a literature review of related literacy concepts, existing definitions of algorithmic literacy, and a qualitative interview study: (1) awareness and knowledge, (2) (critical) evaluation, (3) coping behaviours, and (4) creation and design. Accordingly, algorithmic literacy includes knowledge about the use of algorithms in online environments, an understanding of how they function, the ability to critically evaluate algorithmic selection processes, and practical skills needed to interact with and actively influence algorithmic systems (Dogruel et al., 2021, p. 4).

This can be illustrated using the example of the video streaming service Netflix: A competent user not only recognises that the movie recommendations on the homepage are curated by algorithmic systems but can also assess and reflect on the extent to which this selection steers—or potentially limits—their own decisions and those of others. Finally, they are able to shape the algorithmic curation deliberately, for instance by targeted ratings, searches, or the creation of user profiles, thereby using the platform in a self-determined way.

A major challenge in studying algorithmic literacy is the aforementioned black-box nature of algorithmic systems (DeVito et al., 2018; Hargittai et al., 2020; Oeldorf-Hirsch & Neubaum, 2023). Since even researchers lack full insight into how these systems operate or which indicators influence algorithmic curation, measuring algorithmic literacy in a valid and reliable way remains difficult. This challenge is particularly pronounced when attempting to develop quantitative measurement tools that are transferable across platforms and applications—and remain meaningful amid ongoing system changes. It is therefore not surprising that research into algorithmic literacy has so far been primarily qualitative and exploratory, or limited to specific platforms at particular stages in the development of these dynamic systems (for an overview, see: Oeldorf-Hirsch & Neubaum, 2023, pp. 688–690). Building on the definition outlined earlier, Dogruel and colleagues (2021) develop a standardised scale to assess the cognitive aspects of algorithmic literacy—specifically, awareness and knowledge—in a generalised way applicable to online environments. To measure awareness, respondents are asked to indicate whether various media technologies (e.g., smart speakers) use algorithmic systems. To measure knowledge, they must classify a series of statements as true or false—such as: “The use of algorithms which deliver personalized content can mean that the content you find is mostly consistent with your pre-existing opinions.”

Such broad measurements are especially useful in the context of representative surveys, as they provide a general overview of algorithmic literacy and its development over time. However, given the considerable differences between algorithmic systems, it remains essential to also conduct context- and platform-specific studies—and to examine the extent to which users are motivated to translate their knowledge into action (Riesmeyer et al., 2016). Just because someone knows that their newsfeed is algorithmically personalised—or even how to influence what content appears—does not necessarily mean they act accordingly. For instance, they may not consciously take steps to ensure they are also exposed to content that challenges their views or presents new perspectives on a topic (see also Fouquaert & Mechant, 2021).

To promote algorithmic literacy—which includes not only awareness and knowledge, but also competent action—educational strategies must be developed that go beyond explaining how algorithms work. These strategies should also encourage users to actively and critically engage with algorithmic systems. Oeldorf-Hirsch and Neubaum (2023, pp. 694–695) identify four promising approaches: sparking users' *curiosity* about algorithms, addressing their *motivations* for learning, highlighting areas where they can exert *control*, and offering hands-on *practice* with algorithmic systems. The former, in particular, could also be supported by the platforms themselves—for example, by prompting users to reflect through pop-up messages during content selection (e.g., "Curious why you received this post?"; ibid., p. 694).

As the conclusion will discuss, it is especially important in the context of information use that users critically reflect on the risks of automated, personalised content selection—and avoid relying exclusively on recommendation algorithms when engaging with news and (political) information.

4 Conclusion and Outlook

4.1 Implications of media use in algorithmic environments

The "algorithmic turn" (Napoli, 2014) of recent years has sparked growing concerns about increasing fragmentation, polarisation and radicalisation of discourse—particularly in the public debate (for an overview, see Geiß et al., 2018; Rau & Stier, 2019; Stark et al., 2021). Referring to the now widely known buzzwords "filter bubbles" and "echo chambers"[3], critics have warned

[3] The terms "filter bubble" and "echo chamber" are often used interchangeably—particularly in non-academic discourse—to describe dysfunctional distortions within algorithmic media environments. However, while related, they refer to distinct phenomena. The term echo chamber is more closely linked to mechanisms of *explicit* personalisation and is rooted in a group dynamics perspective. It suggests that individuals actively surround themselves with like-minded others online, leading to mutual reinforcement of shared opinions and a narrowing of political perspectives. In contrast, the term filter bubble is more associated with *implicit* personalisation and reflects a more technology-deterministic

that users may enter—or be placed into—media environments where they encounter only content that reinforces their existing interests and beliefs, thereby deepening opinion entrenchment (Stark et al., 2021, p. 303). These concerns are particularly salient in relation to automated personalisation in the context of political information use. However, scholars have also pointed to risks stemming from entertainment-focused media consumption in algorithmic environments (Schweiger et al., 2019, p. 120).

At first glance, these concerns may appear plausible. As noted earlier, profit-driven algorithmic platforms aim to maximise (advertising) revenue by prioritising content that generates engagement—typically, content that aligns with users' personal interests and viewpoints. But does this mean users are exposed only to topics they enjoy and opinions they already agree with? Current research suggests that such fears may be largely overstated, and that the dangers associated with filter bubbles and echo chambers tend to be exaggerated (see Möller, 2021; Stark et al., 2021). This does not mean, however, that risks are absent. For certain users—particularly those with specific personality traits or media usage patterns—the likelihood of encountering ideologically narrow or thematically repetitive content streams increases. Crucially, such outcomes result not only from algorithmic systems but also from individual choices and selective engagement. This reinforces the importance of promoting algorithmic literacy—not only to foster understanding of how these systems function, but also to enable users to engage with media in more conscious and diverse ways.

In the context of public debate, it may be more constructive to move beyond exaggerated fears and toward a more nuanced examination of how algorithmic media environments shape information ecologies—and what positive or negative roles they play in information use and opinion formation. For instance, better understanding how algorithmic personalisation influences perceptions of the opinion climate or contributes to inequalities in public discourse is essential (Möller, 2021, p. 97; Stark et al., 2021, p. 316). Similarly, discussions should address how recommendation systems could be designed to promote values such as diversity and social relevance, making them viable tools not just for commercial platforms but also for public service media (Schmidt et al., 2018).

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view. It implies that individuals, without actively shaping their media environment, are steered by algorithmic systems into a personalised information ecosystem—ultimately leading to a similarly narrowed worldview. (Hagen et al., 2017, p. 133; Rau & Stier, 2019, p. 402; Stark et al., 2021, pp. 306-307)

4.2 Development and methodological challenges

Recent developments in media usage behaviour underscore the growing importance of algorithmic environments. Algorithms not only shape the selection of media content but also influence users' emotional and cognitive engagement through processes of prioritisation and emphasis. All indicators suggest that the trend toward automated personalisation will continue—and likely intensify (Schweiger et al., 2019, p. 120). Given the ongoing success of social media platforms, streaming services, and similar offerings, one might ask whether non-algorithmic media use remain possible at all in the future.

Communication science is tasked with continuously analysing how various algorithmic environments shape media use, how users navigate them, and—crucially—how the interaction between platform logics and human behaviour determines which content receives attention and potentially influences thoughts and actions. This task poses distinct methodological challenges. If each user is exposed to a unique and dynamic selection of content—one that may change with every new access—how can media use be studied in a reliable manner?

Much of the discussion so far has focused on how to determine what content users actually encounter in algorithmic environments (for an overview, see: Haim, 2020). Promising approaches include collecting primary data through data donations[4] or using browser plug-ins that automatically track the posts shown to individual users on social media platforms (Haim & Nienierza, 2019). However, for those examining media use in the narrower sense—meaning users' actual engagement with content and their cognitive and emotional responses—additional methodological strategies are required. In this context, qualitative approaches offer particular value. These include methods that combine direct observation of usage behaviour with post-exposure walkthroughs (Kümpel, 2019) or think-aloud protocols (Freiling, 2019) to capture users' experiences and interpretations in real time. Ultimately, a comprehensive understanding of media use in algorithmic environments requires mixed-methods designs that integrate both quantitative-computational and qualitative-reconstructive approaches.

[4] The basic idea behind data donations is that users voluntarily share information about their use of digital platforms and services for research purposes, by exercising their right—guaranteed under the GDPR—to request access to the data collected about them (Boeschoten et al., 2020).

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