What Do We Know about Algorithmic Literacy?

The Status Quo and a Research Agenda for a Growing Field

Anne Oeldorf-Hirsch,[1] German Neubaum[2]

[1]Department of Communication, University of Connecticut

[2]Department of Computer Science and Applied Cognitive Science, Universität Duisburg-Essen

Authors' Original Version (Preprint)

Updated May 2023

Author Note

Anne Oeldorf-Hirsch https://orcid.org/0000-0002-3961-3766

German Neubaum https://orcid.org/0000-0002-7006-7089

Correspondence concerning this article should be addressed to Anne Oeldorf-Hirsch, Department of Communication, University of Connecticut, 337 Mansfield Rd Unit 1259, Storrs, CT, 06269. Email: anne.oeldorf-hirsch@uconn.edu

Abstract

The increasing role of algorithms shaping our use of communication technology – particularly on social media – comes with a growth of empirical research attempting to assess how literate users are regarding these algorithms. This rapidly emerging field is marked by great diversity in terms of how it theorizes and measures our understanding of algorithms, due in part to the opaque "black box" nature of the algorithms themselves. In this review article, we summarize the state of knowledge on *algorithmic literacy*, including its definitions, development, measurement, and current theorizing on human-algorithm interaction. Drawing on this existing work, we propose an agenda including four different directions that future research could focus on: 1) balancing users' expectations of algorithmic literacy with developers' responsibility for algorithmic transparency, 2) methods for engaging users in increasing their literacy, 3) further developing the affective and behavioral facets of literacy, and 4) addressing the new algorithmic divide.

Keywords: Algorithmic literacy, algorithmic divide, social media, user engagement, research agenda

What Do We Know about Algorithmic Literacy?

The Status Quo and a Research Agenda for a Growing Field

Algorithms determine nearly everything we do online, from shopping to the news we read to the music we stream. Broadly, algorithms make decisions about what information we see, and they learn this at least partly from our interactions with existing content. On social media specifically, “algorithms are a way of sorting posts in a user’s feed based on relevancy instead of publish time” (Barnhart, 2021). For instance, Facebook uses a machine learning algorithm that ranks posts on numerous factors such as post relevance to determine which to show on a user’s Timeline (Tech@Facebook, 2021), and Twitter uses a similar deep learning algorithm based on factors such as which tweets users engaged in previously (Koumchatzky & Andryeyev, 2017). Even within the scope of social media platforms, the pervasive role of algorithms has the power to influence how informed and connected we are to others in our network based on the content we are presented. Yet, the exact algorithmic formulas are generally kept secret; most websites, apps, and social media platforms only vaguely reveal why users receive the content they do.

Even without knowing the nuances of why every post has appeared in their feeds, it is imperative that social media users understand broadly how their social media content reached them and how it may be influencing them. Users’ skills to find, consume, evaluate, and produce information through media have long been examined under the umbrella term “media literacy” (Livingstone, 2004). On this basis, scholars started using concepts such as “computer literacy” (Horton, 1983), “digital competence” (Janssen et al., 2013), “information literacy” (Johnston & Webber, 2005), “new media literacy” (Koc & Barut, 2016), or “social media literacy” (Festl, 2021) to describe people’s cognitive, technical, and emotional abilities for effectively using newly emerging information and communication technologies.

While many of those concepts cover users' skills to understand how information is created and processed by intelligent systems, a very young strand of research has just started focusing specifically on whether and how people make sense of the algorithms filtering this information. Works addressing this very specific form of digital literacy initially showed that as algorithmic awareness (i.e., basic awareness of the existence of algorithms) is increasing (e.g., Klawitter & Hargittai, 2018), those without this awareness may be disadvantaged by missing out on important information that is not prioritized for them (Rainie & Anderson, 2017). Therefore, those with even more advanced levels of *algorithmic literacy* – not just being aware of the presence and the impact of algorithm-based systems, but also knowing how to use this understanding (DeVito, 2021) – present a new digital divide (Cotter & Reisdorf, 2020; Gran et al., 2021). Therefore, it seems that the prevalence of this specific form of literacy also follows the principles described in well-established digital inequality frameworks (Reisdorf & Blank, 2021).

Hamilton et al. (2014) first called for a framework for exposing algorithms to users and working with them to study their effects. Since then, researchers have increasingly taken up the call to assess if and how well social media users understand these algorithms. Such research is difficult because the actual algorithmic working is unknown even to the researcher and requires interpretation (Andersen, 2020; Kitchin, 2017; Latzer & Festic, 2019). This limits the ability to assess how "correct" users are in their understanding (Koenig, 2020). In other areas of digital literacy, such as web skills, clear answers exist about what a user knows (e.g., what a bookmark or a PDF is; Hargittai, 2009), whereas the secretive nature of algorithms makes it difficult to assess literacy about them. Therefore, the current problem is two-fold: 1) What is algorithmic literacy? and 2) How do we assess this?

The purpose of this paper is to define algorithmic literacy, based on existing research, review current issues in algorithmic literacy, and propose an agenda for moving forward with algorithmic literacy research. Festic (2020) points out that algorithmic selection is now a significant aspect of everyday life. Algorithms exist in many forms, including search, filter, recommendation, and scoring algorithms, which have differing functions across various contexts. Festic summarizes these contexts in four life domains: Social and political orientation, recreation, commercial transactions, and socializing. Social media apps may span all of these life domains, as they offer spaces to socialize, find news, watch videos and other entertainment, and make purchases among users. However, individuals turn to social media largely to interact with others. In these spaces, algorithms lead users to content from their friends, family, or other social connections, driving how they engage with those individuals. For instance, users may expect to see all content their social connections post, but algorithms filter and prioritize what is displayed in their feeds.

Therefore, our focus is primarily on social media content filtering algorithms. Uncovering users' handling of filtering algorithms in social media appears of pivotal relevance, as algorithmic filtering is supposed to shape the balance of users' information landscape (e.g., via "curated flows") and, in turn, their political attitudes and actions (Klinger & Svensson, 2018; Ohme, 2021; Thorson & Wells, 2016). Second, filtering algorithms might be the type which is most salient in social media users' awareness, as it plays a key role in public debates and becomes more and more important in social media platforms (e.g., TikTok). Thus, we are interested in the user experience with these filtering algorithms as they use social media apps.

To construct this review, we searched for literature using the search term "algorithmic literacy" and related terms, including "algorithmic awareness," "algorithmic knowledge," "algorithmic understanding," "algorithmic experience," "algorithmic skills," "algorithmic divide," and "algorithm" + "belief." We started our search in Google Scholar, then focused more specifically on the Communication and Mass Media Complete, PsycInfo, and ACM Digital Library databases. Our search strategy moved from narrow to broader; first searching the terms in the title, then the abstract, and then the full text. Upon reviewing abstracts, we determined if the article empirically assessed or theorized Internet users' understanding of or interaction with algorithms. Finally, we included additional relevant articles cited by these initial articles. In total, we reviewed 96 articles that were deemed potentially relevant, 50 of which are included in this review.

Defining Algorithmic Literacy

Algorithmic literacy has recently been defined in two ways. First, as "the capacity and opportunity to be aware of both the presence and impact of algorithmically-driven systems on self- or collaboratively-identified goals, and the capacity and opportunity to crystalize this understanding into a strategic use of these systems to accomplish said goals" (DeVito, 2021, p. 3). Second, as "being aware of the use of algorithms in online applications, platforms, and services, knowing how algorithms work, being able to critically evaluate algorithmic decision-making as well as having the skills to cope with or even influence algorithmic operations" (Dogruel et al., 2021, p. 4). Both definitions attempt to incorporate the evolution of many sub-dimensions of algorithmic understanding. The first proposes two broad stages of understanding, from mere awareness to practical use. The second expands literacy to four steps, by distinguishing awareness from knowledge, adding the ability to critique algorithms, and the skills to influence them. While these definitions offer necessarily nuanced definitions of literacy, they propose different levels of granularity in terms of what constitutes "literacy" comprehensively.

A Short History of Defining Algorithmic Understanding

Initially, research focused on the concept of *algorithmic awareness*: that users are even aware of the existence of algorithms. It has since been more explicitly defined as "knowing that a dynamic system is in place that can personalize and customize the information that a user sees or hears" (Hargittai et al., 2020, p. 771). In attempts to address more than just awareness, other researchers focus on *algorithmic knowledge*. Cotter and Reisdorf (2020) note that while "basic awareness provides a foundation on which to build an understanding of the criteria by which algorithms rank content…more advanced algorithmic knowledge includes insight about the principles and methods of software development that underlie algorithms and/or the social and political effects of algorithms" (p. 747). Finally, *algorithmic skill* refers to "users' knowledge about algorithms and their role in making online content visible, as well as users' ability to figure out how particular algorithms work, and then leverage that knowledge when producing and sharing content" (Klawitter & Hargittai, 2018, p. 3492).

Swart (2021a) categorizes experiences with algorithms into cognitive, affective, and behavioral dimensions, where *understanding* algorithms represents the cognitive comprehension of their existence and functioning, *sensing* algorithms represents the affective influences that algorithms have over users, and *engaging with algorithms* represents the behavioral dimension of interactions with algorithms. This aligns similarly to Lomborg and Kapsch's (2020) framework of *knowing*, *feeling*, and *doing* algorithms.

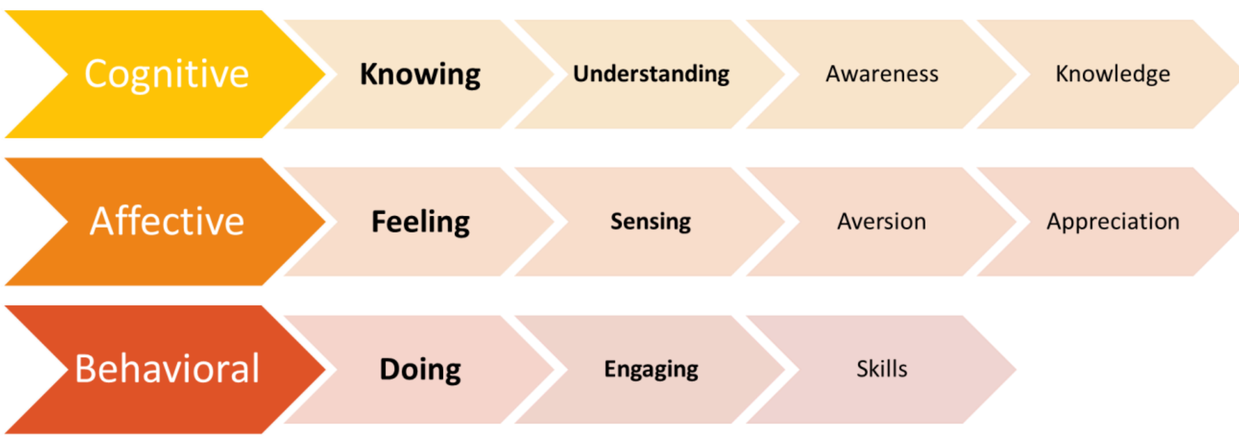
Dogruel, et al. (2021) place both awareness and knowledge in the *cognitive* dimension of understanding algorithms, separate from a *behavioral* dimension, which includes coping with algorithms and using them for creation. Cotter (2022) taps into the behavioral by proposing a practical knowledge of algorithms, "to capture knowledge located at the intersection of practice and discourse" (p. 2). This is similar to the use of skills (Klawitter & Hargittai, 2018), though the ambiguity of algorithms offers no concrete proof of how skilled a user is in using them, highlighting a boundary condition of behavioral understanding. Finally, an *affective* dimension has developed largely in the literature of attitudes toward algorithms. Specifically, research pits *appreciation* (preferring an algorithm over a human in decision-making; Logg et al., 2019) against *aversion* (preferring a human over an algorithm; Dietvorst et al., 2015). Though not explicitly about understanding algorithms – rather focusing on how individuals feel about them – these affective components also imply awareness, and potentially some component of skill.

The short but varied history of algorithmic definitions represents both a range of concepts that are being addressed (e.g., awareness vs. skills), and may also highlight terminological inconsistencies that need to be addressed for the field to move forward cohesively. We advocate for further converging on *algorithmic literacy*, such as has been defined by DeVito (2021) and Dogruel, et al. (2021), as an umbrella term. However, we must decide whether to cultivate a cohesive definition of literacy as an overarching construct, or accept definitions as collections of other concepts that make up literacy.

Previous iterations of literacy (e.g., media, information, Internet, digital, and social media literacy), are also multi-faceted, incorporating elements of their previous literacies. For instance, a recent systematic review of social media literacy (Polanco-Levicán & Salvo-Garrido, 2022) concludes that its definition takes media literacy and adds elements pertinent to social media, which overlap but do not encompass digital literacy. Yet, no one definition of social media literacy rises to the surface. Instead, definitions vary from those that tap into cognitive, affective, and behavioral elements to those which address increasingly complex stages of understanding. Settling on one definition of *algorithmic literacy* will prove just as difficult. In any case, we can similarly categorize the existing and emerging cognitive, affective, and behavioral aspects of understanding, and further define boundaries between them. Moving forward, this allows the development of literacy frameworks, which can address literacy gaps and lead to interventions along the lines of previous literacy research in communication technology. As a first step, we have visualized the current definitions in Figure 1.

Figure 1

Dimensions of algorithmic literacy.



Shifting Divides in Algorithmic Literacy of Social Media Users

The implementation of algorithms in social media sets a starting point for dividing users who know about them from users who do not, driving gaps that have impacts in areas from politics (Huszár et al., 2022) to e-commerce (Klawitter & Hargittai, 2018) to community (DeVito, 2021). Facebook was the first social media platform to start experimenting with an algorithm on its newly created News Feed in 2007 (Wallaroo Media, 2021). This led to EdgeRank, Facebook's first algorithm, which showed News Feed content based on a variety of factors, including relationships, "weight" of each item, and time decay (Bucher, 2012). This has since been replaced by a more sophisticated and constantly evolving machine learning algorithm to curate highly personalized content (Tech@Facebook, 2021). Twitter implemented its Timeline algorithm in 2016, switching to an "optimized" (rather than chronological) feed by default (Koumchatzky & Andryeyev, 2017), and Instagram followed suit the same year (Titcomb, 2017). Most recently, TikTok revealed in 2020 that its algorithm recommends videos in a user's "For You" feed based on user interactions with other videos, video information, and device and account settings (TikTok, 2020). Each of these algorithms chooses for the user what appears in their social media feed, and not all users know this.

Some of the earliest writing on how social media users engage with algorithms started with Bucher's (2012) Foucauldian analysis of managing visibility on Facebook within its EdgeRank algorithm. This case study illuminated how even the earliest social media algorithms shaped the prevalence of one's content and thus identity in social media spaces. The first empirical work on Facebook users' experiences with algorithms showed that the majority (62.5%) were still not aware that Facebook did not show all available posts in their news feeds, and were surprised or even angry to find out that content was filtered (Eslami et al., 2015). This left most users behind in trying to communicate and manage their online relationships. When asked more openly whether they thought Facebook always showed all their friends' posts, the majority (73%) said no (Rader & Gray, 2015). Yet they did not understand how such filtering worked, or why it was done, which meant they had little power to influence or leverage it. By now, most online news users realize that content is filtered, but still have a limited understanding of the criteria used (Powers, 2017; Swart, 2021b). Similarly, YouTube users show a high awareness of the algorithmic process that recommends content on the platform, but can only guess at what data it uses (Alvarado et al., 2020). In both cases, this leaves users guessing at how to get to the content they want or how to get their content to desired audiences. Notably, TikTok users feel acutely aware of the algorithms that shape their "For You" page and state that they regularly "train" the algorithm to show desirable videos (Siles & Meléndez-Moran, 2021), though the accuracy of this is difficult to determine given the opaque nature of algorithms.

In any case, even those actively invested in understanding algorithms can only glean so much from their interactions with them. Independent artists on sites such as Etsy recognize the importance of algorithms, and find ways to learn about taking advantage of them (e.g., by testing out various search optimization strategies), but are ultimately frustrated with their lack of verified knowledge (Klawitter & Hargittai, 2018). YouTube content creators engage in "algorithmic labor" to negotiate the opacity and precarity of the platform's advertising moderation algorithms (Ma & Kou, 2021). Instagram influencers are also acutely aware of algorithms, but lack definitive information about their functioning, so they take it upon themselves to "play the visibility game" by testing the outcomes of various engagement behaviors (Cotter, 2019).

For marginalized communities, not being able to grasp onto the algorithm is equally important, and can have serious social consequences. LGBTQ+ Facebook users carefully navigate algorithms to manage their self-presentation in online spaces subject to context collapse, yet must continually re-theorize how these changing algorithms work (DeVito, 2021). Similarly, on TikTok, LGBTQ+ users never feel fully in control of their digital self-presentation, because while the algorithm is highly personalized, it cannot be tamed, leaving users unable to integrate their various selves (Simpson et al., 2022). Thus, while algorithmic literacy of social media platforms has increased markedly within the past decade, users may be reaching the limits of what they can know without greater algorithmic transparency, and are facing the consequences.

Inductive Routes to Algorithmic Literacy

Given the limited available knowledge about how algorithms work, users can only develop their own ideas about what algorithms might be. Bucher (2017) calls this interaction between people and algorithms an *algorithmic imaginary*, or the "way in which people imagine, perceive and experience algorithms and what these imaginations make possible" (p. 31). These are not false beliefs, but the best understanding that users can develop based on their own experience with algorithmic spaces such as Facebook. For example, users may notice a commonality between their social media behavior and target ads and theorize how these are connected.

Based on such repeated experiences, users develop folk theories, or "intuitive, informal theories that individuals develop to explain the outcomes, effects, or consequences of technological systems, which guide reactions to and behavior towards said systems" (DeVito et al., 2017, p. 3165). These folk theories are malleable, adapting to accommodate algorithmic changes on the platforms (DeVito, 2021). Most social media users develop folk theories based on their own experiences within a platform (*endogenous information)*, such as patterns of who and what appears in their feeds. This is complemented by *exogenous information*, such as media reports or discussions with other users.

Algorithmic folk theories are both general and platform-specific. For instance, Facebook users developed several theories about algorithms in their feeds, based on their experiences on that site (Eslami et al., 2016). Most followed a *personal engagement theory* that the more they interact with someone, the more they show up in their feed. Others ascribed to the *global popularity* theory (content with more likes is more likely to show up in their feed), *format theory* (posts with media content get higher priority), or *narcissus theory* (users see content from those similar to themselves). However, Spotify folk theories (Siles et al., 2020) reveal that users estimate how the Spotify algorithm works based on their understanding of other algorithms (e.g., Netflix recommendations) and also based on that platform's specific features in contrast to competitors (e.g., Apple Music). On YouTube, users' beliefs vary widely about how content is presented to them, among which there is no explicit agreement (Alvarado et al., 2020). On TikTok, users focus on how content could reach *other* users' feeds based on their own engagement (Klug et al., 2021).

Gaps and Biases in Algorithmic Literacy

Although some social media users have developed a rich understanding of algorithms, this also presents the risk for a growing divide, akin to those seen with other technologies (e.g., Internet access). Initial research on algorithmic literacy gaps shows that those with less developed technological (specifically, search engine) skills also showed lower algorithmic knowledge (Cotter & Reisdorf, 2020). Yet even those with higher formal education may be missing this technology-specific knowledge. A recent report shows that college students are no longer prepared for the information landscape that exists today, as assignments do not address the necessary technological skills (Head et al., 2020). While most of these students indicated an awareness of algorithms, most had no idea how they worked or what their effects would be. With most of the online content that users engage with now controlled by algorithms, a lack of information literacy implies a lack of algorithmic literacy, with detrimental implications.

Another common factor in algorithmic literacy, as with most digital literacies, is the effect of age (Cotter & Reisdorf, 2020; Gran et al., 2021), with younger Internet users showing more algorithmic knowledge than older users. This may disproportionately leave older social media users at higher risk for misinformation or information exclusion. This pattern can already be seen in terms of how different generations handle misinformation online, with reports indicating that older users are worse at recognizing misinformation, and have a greater hand in spreading it (Gottfried & Grieco, 2018). With algorithmic literacy at stake, those with already lower algorithmic literacy can be further adversely affected with reduced or biased information access in their social media feeds. For example, not understanding that an algorithm is dictating what appears in one's Facebook feed could lead a user to believe that the limited political information they are seeing is the whole and accurate political reality.

More insidiously than just not showing users the full scope of information, algorithms *systematically* bias content for users, excluding entire groups from receiving information or being represented by it. This happens when Google shows ads for higher-paying jobs disproportionately to men over women (Kirkpatrick, 2016), or when Facebook targets their housing ads so as to exclude certain racial, religious, disabled, and other protected classes of people (Booker, 2019). Worse yet, algorithms can make detrimental assumptions about users in a process called *algorithmic symbolic annihilation*, such as when individuals who have experienced pregnancy loss continue to be subjected to content about pregnancy (Andalibi & Garcia, 2021).

Unfortunately, algorithms do not merely reflect existing biases, but further perpetuate them through their own design. Danks & London (2017) taxonomize routes to algorithmic bias, putting *interpretation bias*, or how the algorithm presents information to the user, at the end. As they point out, algorithms are biased through many earlier steps, starting with learning from biased input data. For instance, facial recognition software – now widely understood to be biased against women and people of color – is likely built on training datasets that disproportionately feature white male faces (Garvie & Frankle, 2016). This could mean dominant groups receiving even more opportunities than already marginalized groups. While this problem expands beyond mere literacy, awareness of these biases is the first step in correcting them.

Initial Theorizing of Human-Algorithm Interaction

Building a comprehensive framework of algorithmic literacy is difficult because of the ever-changing nature of algorithms, but there are some attempts to move toward a more cohesive study of algorithmic experiences. Just as approaches to understanding algorithmic literacy come from communication and computer science, among other fields, so do attempts to build frameworks for improving literacy based on the algorithm-user relationship.

From a communication perspective, Lomborg and Kapsch (2020) adapt the communication theory of decoding to developing an understanding of algorithms. The purpose of this approach is to highlight the gaps in knowledge that must be interpreted for meaningful communication, in this case about and with algorithms. Because algorithms cannot be directly decoded, users attempt to decode them through communication processes of knowing, feeling, and doing algorithms. To *know* an algorithm is to be aware of its presence and basic functioning, which varies greatly between individuals, and comes from a combination of formal learning, personal experiences, and third-party media and conversations. Through encounters with algorithms, users also *feel* them. As illustrated by earlier work on appreciation (e.g., Logg et al., 2019) and aversion (e.g., Dietvorst et al., 2015), these experiences can be positive or negative, but only if the algorithm becomes noticeable, which most often it does not. Users *do* algorithms by interacting with them through digital media in three particular ways: using them as intended by effectively feeding them data through usage, cautiously engaging with them as a necessary but imperfect part of information systems, or actively resisting them as problematic technologies.

These three stages of decoding algorithms synthesize nicely the existing research on awareness of algorithms (knowing), and attitudes about algorithms (feeling), and points to necessary future work on assessing the effects of algorithmic literacy on behaviors (doing). In particular, it provides a framework for linking attitudes with behaviors, namely in proposing that the dominant, negotiated, or oppositional ways that users engage with algorithms is determined by holding positive, mixed, or negative views of algorithms, respectively. By incorporating how users feel about algorithms, future research on improving literacy can tailor interventions to users based on their existing awareness and attitudes.

From a technical user experience perspective, Alvarado and Waern (2018) propose Algorithmic Experience (AX) as an analytical framework for making user interactions with algorithms more explicit. The framework contains five dimensions, the purpose of which are to increase algorithmic awareness and empowerment. *Algorithmic awareness* is the general understanding that algorithms are present, which guides the other dimensions. *Algorithmic profiling transparency* refers to the extent to which a system makes visible what it knows about a user and how it uses that information to present information. *Algorithmic profiling management* considers how much input users could have in managing the profiling done by an algorithm. *Algorithmic user control* refers to the various ways a system could give users control over its algorithm, such as changing the display of news feed items, turning off data sources, or giving feedback when the algorithm makes a faulty prediction. *Selective algorithmic memory* expands on user control to specifically allow users to determine what data algorithms get to use to make their predictions.

This framework provides a jumping off point for interventions to increase algorithmic literacy. For instance, profiling transparency could be displayed in real-time social media use to increase algorithmic awareness, and profiling management could further test a user's algorithmic knowledge. User control could be implemented as various engagement points that improve algorithmic skills. Finally, selective memory might be the result of clearer profiling, management, and control that influences key attitudes about algorithms and resulting behaviors.

Investigating Algorithmic Literacy

As Kitchin (2017) notes, researching users' understanding of algorithms is challenging because algorithms are 1) largely inaccessible, 2) highly varied from platform to platform, and 3) constantly changing. First, platforms that depend on user data (e.g., Meta) do not reveal how their algorithms work. Second, other platforms (e.g., Twitter and TikTok) may function on largely different sets algorithms, meaning that even if one is revealed, it may not usefully inform users of another. Third, algorithms are dynamic by design, continuously learning from user data to improve their output, so insights are not relevant for long. Furthermore, as Seaver (2019) notes, knowing an algorithm is not as simple as achieving algorithmic transparency, but in understanding *algorithmic systems* that function as an interplay between humans and computers within broader social, cultural, and political contexts. This further complicates researchers' attempts to determine how much users know.

Given this, Hargittai, et al. (2020) set out guidelines for what may or may not work for assessing these "black box" measures. For instance, directly asking social media users to report their level of literacy is unlikely to be useful, but instead more in-depth discussions of their experiences with algorithms may uncover what they really know. This returns us to the point that algorithmic literacy is not simply algorithmic awareness, or even knowing *what* algorithms are, but also feelings toward algorithms and ways of using them.

Methodological Starting Points

Methods for studying algorithmic literacy currently use qualitative approaches (e.g., focus groups; Siles et al., 2020) and quantitative approaches (e.g., surveys; Cotter & Reisdorf, 2020). Naturally, each method offers a unique lens for assessing algorithmic literacy, while also presenting limitations. Whereas strengths and weaknesses exist for all research methods, this problem is particularly salient for algorithmic literacy, where the opacity of algorithms makes arriving at a "ground truth" of assessing their functions impossible (Hargittai et al., 2020). Given this, much of the research has been exploratory thus far, with recent attempts to move into testing more uniformly defined measures of literacy (Dogruel et al., 2021; Zarouali et al., 2021).

Knowledge of algorithmic experiences was built on qualitative methods such as in-depth interviews, leading to the development of folk theories about Facebook (Bucher, 2017), Google News (Powers, 2017), YouTube (Alvarado et al., 2020), Spotify (Siles et al., 2020), and TikTok (Klug et al., 2021). These methods allow participants to express a wide range of emotions about and expectations of with algorithms in their own use, which can also vary widely by platform. However, given unique user experiences across platforms, this method also limits the ability to draw broader common inferences about an algorithmic experience.

Conversely, the move to quantitative survey approaches provides a generalizable method for testing literacy as a predictor or outcome, but their unified measures sacrifice unique user experiences. For example, surveys measuring algorithmic knowledge are able to show that education and search skills are positively correlated with algorithmic knowledge (Cotter & Reisdorf, 2020), and negatively correlated with online news engagement (Makady, 2021). These studies provide new insight into what might predict or be predicted by algorithmic literacy, though with a necessarily narrower understanding of the concept.

One method in need of development are experimental studies of algorithmic literacy effects on various cognitive, affective, and behavioral outcomes. One such intervention has tested the effects of exposure to algorithmic information and found changes to users' attitudes about algorithms (Silva et al., 2022). Computational approaches are another avenue for more advanced assessments of algorithmic literacy, potentially through the collection and display of social media data to its users for reflection.

Measuring Algorithmic Literacy

Dogruel, et al.'s (2021) algorithmic literacy scale is currently the most comprehensive attempt to measure literacy, capturing the dimensions of algorithmic awareness and algorithmic knowledge. Algorithmic awareness is measured using binary statements about whether a variety of communication technologies (e.g., Internet browsers) use algorithms to function. Algorithmic knowledge uses true/false statements to measure more nuanced aspects of algorithms, 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" and "I can influence algorithms with my Internet usage behavior" (Dogruel, Online Supplement). This scale takes a useful step forward in assessing literacy, though still breaks into two sub-scales that together do not measure algorithmic literacy as one cohesive construct.

Aside from this scale, most research has focused on investigating algorithmic awareness or algorithmic knowledge separately, though each is not uniformly operationalized. So as to avoid priming effects, awareness is often gauged indirectly by asking users open-endedly about their general experiences with algorithmically-driven platforms with hopes that indicators of algorithmic awareness arise (e.g., DeVito et al., 2018; Schwartz & Mahnke, 2018). Awareness has also been addressed through somewhat more focused questions, leading users to speculate about why content is presented to them, but still usually without explicit reference to algorithms (e.g., Koenig, 2020; Powers, 2017; Rader & Gray, 2015). In the most direct measure, Gran, et al. (2021) ask survey participants to self-report their awareness with the question “What kind of awareness do you have that algorithms are used to present recommendations, advertisements and other content on the Internet?” (p. 18).

Zarouali et al. (2021) provide a more developed quantitative measure of awareness with their Algorithmic Media Content Awareness (AMCA) scale. This scale measures the level of awareness of four constructs of algorithmic media platforms: content filtering, automated decision-making, human-algorithm interplay, and ethical considerations. One drawback of this scale is that it relies on users to assess their awareness of each construct for a specific platform, rather than generally. To date, no published researched has used the scale for platforms beyond those tested in its original development (Facebook, Netflix, and YouTube), leaving open the question of whether content differs for other platforms (e.g., Instagram, Twitter) or is truly generalizable across all algorithmic media content.

Cotter and Reisdorf’s (2020) measure of algorithmic knowledge asks participants to rank how much influence they feel various actions have on their search engine results. This differs from knowledge measures Zarouali et al. (2021) validated against awareness in their AMCA scale, which used true/false statements about common algorithmic misconceptions. Their evidence indicates that algorithmic awareness and algorithmic knowledge are positively correlated, but remain distinct concepts. Therefore, rather than focusing on distinguishing or combining concepts, future research should focus on further developing frameworks that incorporate sub-dimensions, such as those proposed by Swart (2021a) and Lomborg and Kapsch (2020).

Moving Forward with Algorithmic Literacy Research: An Agenda

The previous systematic overview of theoretical and methodological research on literacy, awareness, and attitudes toward algorithms indicates that studies from various disciplines have started focusing on how humans perceive, explain, and evaluate the functionalities of algorithms. We believe that a promising way to move this line of research forward is to consider algorithmic literacy in different roles within the process of human-technology interaction: a) as predictors of users' evaluations of algorithms and their interaction with them, b) as a moderator and/or mediator indicating when this form of literacy can exacerbate or attenuate technology effects, and c) as a dependent variable by asking how it can be changed. Taking these three roles into account, we propose a research agenda within the framework of human-algorithm interaction focused on four key areas: 1) balancing algorithmic literacy with algorithmic transparency, 2) engaging users in increasing their literacy, 3) developing the affective and behavioral facets of literacy, and 4) addressing the algorithmic divide.

Balancing User Literacy and Platform Transparency

We believe that – as one of the main purposes of research – the omnipresence of algorithms in social media users' daily lives requires communication scholars to consider the relationship between users and algorithm creators, particularly in terms of the responsibility that each has in promoting literacy. Following the ideas of human-algorithm interaction approaches (Alvarado & Waern, 2018; Lomborg & Kapsch, 2020; Swart, 2021a), we argue that algorithmic systems need to represent both entities – the human and the algorithm – and describe how their interaction can shape algorithmic literacy. More specifically, researchers need to specify both what users need to understand, and which technological cues or properties are accessible to users to support this understanding. Much of the focus this far has been on the literacy needs of social media users, yet there is also pressure on app developers for *algorithmic transparency*.

In their innovative intervention, Rader, et al. (2018) test short explanatory statements that reveal key elements of the Facebook algorithm, including what, how, and why information ends up in their feeds. They find evidence that viewing these statements increased users' understanding of what algorithms are and how they function. Notably, it often presented new and surprising information to users, indicating that average social media users still have a lot to learn about algorithms, but that even a little bit of information from the app itself can have a significant impact on their understanding. Some apps do provide various levels of *algorithmic cues* for why content appears in a feed, such as "because you interacted with a post from this user" on Instagram or "Sara celebrated this post" on LinkedIn, yet it is not yet known which cues are displayed to which users, and whether they are noticed at all.

The Algorithmic Experience framework (Alvarado & Waern, 2018) outlines which psychological processes operate when individuals interact with each of these technological cues and properties. Besides identifying these processes, an applied literacy/design approach could specify how different manifestations of those cues (explicit or implicit recommendations) form different dimensions of algorithmic literacy (e.g., awareness, knowledge, interaction skills). This theoretical endeavor should also include key variables that significantly shape the level of algorithmic literacy besides the actual human-algorithm interaction such as general technological experience (e.g., search engine skills; Cotter & Reisdorf, 2020).

Algorithmic folk theories play an important role here in understanding how social media users understand, feel about it, and engage with algorithms, from their perspective. While folk theories can vary in accuracy, they shed light on users' subjective experiences with algorithmic environments, which affect their attitudes and behaviors around algorithms. Crucially, they highlight what users do and do not perceive in terms of algorithmic transparency, which offers important insights for designers who make choices about what algorithmic cues to make visible on their interfaces. Previous works specified which folk theories users of specific platforms develop based on interrelationships between behavior and the consequences they observe (e.g., DeVito, 2021; Eslami et al., 2016; Lee et al., 2022; Ytre-Arne & Moe, 2021) and which kind of sources they use to develop these lay assumptions (DeVos et al., 2022). Still, future research needs to observe to what extent different levels of algorithmic transparency (manifested through cues) can provoke certain cognitive, affective, and behavioral responses reflecting a certain level of algorithmic literacy.

Engaging Users in Algorithmic Literacy

Having proposed that algorithmic literacy should not be solely the responsibility of the social media user, the current reality is that individuals must endure most of effort in improving literacy. Therefore, it seems commendable to develop and customize interventions that increase users' engagement in their own literacy. Especially in the face of potential behavioral calculus (Dienlin & Metzger, 2016), a higher level of algorithmic literacy seems pivotal for users to make informed and well-reasoned decisions about which actions they wish to show and which information they desire to disclose when using emerging communication technologies. Building on the current empirical work – particularly that on folk theories (e.g., DeVito, 2021; DeVito et al., 2017; Eslami et al., 2016) – four key psychological concepts seem particularly important to consider in engaging users in this process: 1) curiosity, 2) motivation, 3) control, and 4) practice. These reflect individual, situational, attitudinal, and behavioral aspects.

Curiosity

First, learning about algorithms seems aided greatly when curiosity is triggered (e.g., Siles & Meléndez-Moran, 2021). While most social media users are now aware of the existence of algorithms (Lomborg & Kapsch, 2020), this is not enough to provoke greater literacy. Instead, users likely need to be curious about what the algorithms do and why. Curiosity may be a set personality trait, but could be encouraged in certain social media contexts. Bucher (2017) finds that many Facebook users first learn about algorithms in unexpected encounters or “whoa moments,” such as when they realize a social media ad has “found them” from previous interactions. Rather than make these encounters “creepy,” they could employ algorithmic cues about why the content in question found them. Previous research indicates that brief explanatory mechanisms could be effective in increasing literacy (Rader et al., 2018). To spark curiosity about algorithms, a pop-up notification could appear when users engage with a post, asking “curious why you received this post?” and providing an opportunity for users to learn more.

Motivation

Second, motivation may be crucial, as passive social media users are not as likely to care why certain content appears on their social media apps. Yet, more active users such as content creators, influencers, and those who otherwise use social media to meet specific goals have a vested interest in learning how the algorithm filters content. For example, Etsy artists and YouTube content creators strategize to optimize the algorithm (Klawitter & Hargittai, 2018; Ma & Kou, 2021) for greater earning potential. Furthermore, users in the demographic majority who find themselves well-represented by the content in their feeds may not feel compelled to care how the algorithm works, as it already serves them (e.g., DeVito, 2022). However, users in marginalized groups whose identities are not as prominent in the space – especially when they are actively fighting for recognition through movements such as Black Lives Matter or #MeToo – are likely to be more motivated to understand how an algorithm could filter out their presence. Thus, finding each user's motivations for engaging with content on a social media platform could be a vital step in determining what and how to increase their algorithmic literacy.

Control

Third, to the extent that users possess a greater locus of control, or feel they have more influence on the algorithm, the more likely they may be to engage with and learn from it. Previous research finds that users appreciate algorithms more when they are given even a little control over it (Dietvorst et al., 2018). This seems particularly true in the case of the TikTok algorithm, where a user's sense that they have some influence on it plays a role in their enjoyment of the platform, and indicates a deeper algorithmic understanding than on other platforms (Siles & Meléndez-Moran, 2021; Simpson et al., 2022). While platforms determine how much influence (if any) users can have on their algorithm, users could be made aware about where they have some influence, such as how to prioritize certain friends in one's Facebook news feed or how to turn off personalization of trends on Twitter.

Practice

Finally, users need practice with algorithms to better understand them. Several studies indicate that those who use social media platforms more are more knowledgeable about the algorithms that determine the content shown (Cotter & Reisdorf, 2020; Eslami et al., 2015). Demographic factors such as age and education are also correlated with algorithmic literacy (Gran et al., 2021), providing indirect evidence that those who use social media more (younger, more educated) have greater algorithmic literacy. Practice with algorithms might then be a matter of closing the digital divide, by providing better access to and training on social media, both in formal education contexts and through online learning opportunities while using social media platforms.

Strengthening Affective and Behavioral Facets of Algorithmic Literacy

Currently, measures of algorithmic literacy lie mostly in the cognitive dimension (Cotter & Reisdorf, 2020; Dogruel et al., 2021; Gran et al., 2021; Zarouali et al., 2021), stopping at awareness or knowledge of algorithms. However, broader frameworks (e.g., Lomborg & Kapsch, 2020; Swart, 2021a) note the importance of affective and behavioral dimensions as part of holistic literacy. Knowledge about algorithms is not strongly correlated to positive attitudes (Araujo et al., 2020; Dietvorst et al., 2015; Yeomans et al., 2019), and increasing this knowledge does little to change these attitudes (Silva et al., 2022). This highlights that affective dimensions of literacy function separately from knowledge, and likely depend on users' needs and motivations for using any specific algorithmically driven platform. Indeed, initial evidence indicates that users reflect upon the "platform spirit" and whether this platform's functionalities match their understanding of the system and their motives to use it (DeVito, 2021). Thus, it is crucial to analyze users' individual differences that could intervene in the relationship between algorithmic knowledge and attitudes. For instance, the attitude toward an algorithm that filters information based on the users' political preferences may vary depending on whether users are driven by a defense (i.e., looking for information that support one's viewpoints) or accuracy (i.e., seeking unbiased and balanced information presentation) motivation (Winter et al., 2016).

Knowledge has also long been treated as a key qualification for responsible and desirable user behavior in human-technology interaction (Livingstone, 2004). Still, it is normatively difficult to estimate which behaviors related to algorithms define literacy For instance, is it the user feeding the algorithm with more information so that it becomes more accurate or the user refraining from disclosing information to protect their privacy that is more literate? Again, the desirability of a behavior might be a function of users' individual needs (e.g., their need for privacy; Trepte & Masur, 2020). Users' actions on social media follow a complex calculus of what they gain versus what they lose when disclosing certain types of information (Dienlin & Metzger, 2016). This calculus has implications not only for users' lay perceptions and folk theories about the curation of information they receive but also for their self-presentation as the algorithmic curation can be a barrier in the relationship between self-presenters and their audiences (DeVito et al., 2018; Karizat et al., 2021; Lee et al., 2022). Extending the research focus of algorithmic literacy as predictor of this behavioral calculus will help to uncover when knowledge and awareness transfer to observable actions.

Addressing the Algorithmic Divide

Finally, the pivotal question to further approach the concept of algorithmic literacy and its status quo is: *Who* knows *what* and *why*? This line of inquiry considering algorithmic literacy as a consequence of certain circumstances is clearly associated with the idea of the digital divide and the extent to which technical knowledge and skills vary across different user groups (van Deursen & van Dijk, 2014). A recent study suggested that algorithmic awareness is more prevalent among male and better educated users (Gran et al., 2021). Still, it remains unclear whether these associations are observable in different national contexts and to what extent they are attributable to further factors such as access to and experience with technologies, and users' self-efficacy. Identifying groups within which algorithmic literacy is remarkably low would help to develop tailored interventions to increase users' knowledge and skills related to algorithms and to propose ways to close the algorithmic divide.

That said, future research should not only provide a comprehensive socio-demographic analysis of the prevalence of algorithmic literacy but also focus on “softer” drivers such as access and experience with technology. Likewise, algorithmic divides can also occur based on users’ identities and their construction thereof. Especially users from marginalized groups such as the LGBTQ+ community indicated that personalizing algorithms do not grasp their identities properly, so they face extra challenges in terms of their literacy to make algorithms in constantly changing social systems work for them (DeVito, 2022; Karizat et al., 2021; Simpson et al., 2022). Therefore, users’ personal identities warrant exploration when determining which user groups have extensive versus less knowledge about how algorithms work and why this is the case.

Conclusion

The current state of the research on algorithmic literacy is rich, if still somewhat scattered in its approaches across various fields of study. In the past decade, researchers have uncovered how aware social media users are of algorithms, how they form folk theories, and have begun to develop quantitative assessments of algorithmic literacy. While a comprehensive framework of algorithmic literacy is difficult to develop due to the opaque, heterogeneous, and user-dependent nature of the algorithms being investigated, some attempts exist to synthesize the user experience of algorithms. Still, much remains unknown, such as what predicts algorithmic literacy, its cognitive, affective, and behavioral outcomes, and how to improve it. Thus, we present an agenda for moving forward with algorithmic literacy research, which includes balancing user and developer responsibilities, engaging users in their literacy, further developing behavioral dimensions of literacy, and addressing the algorithmic divide.

References

Alvarado, O., Heuer, H., Vanden Abeele, V., Breiter, A., & Verbert, K. (2020). Middle-aged video consumers' beliefs about algorithmic recommendations on YouTube. *Proceedings of the ACM Conference on Human-Computer Interaction, 4*(CSCW2). https://doi.org/10.1145/3415192

Alvarado, O., & Waern, A. (2018). Towards algorithmic experience. *Proceedings of the ACM Conference on Human-Computer Interaction*, 1–12. https://doi.org/10.1145/3173574.3173860

Andalibi, N., & Garcia, P. (2021). Sensemaking and coping after pregnancy loss: The seeking and disruption of emotional validation online. *Proceedings of the ACM Conference on Human-Computer Interaction*, *5*(CSCW1), 1–32. https://doi.org/10.1145/3449201

Andersen, J. (2020). Understanding and interpreting algorithms: Toward a hermeneutics of algorithms. *Media, Culture & Society*, *42*(7–8), 1479–1494. https://doi.org/10.1177/0163443720919373

Araujo, T., Helberger, N., Kruikemeier, S., & de Vreese, C. H. (2020). In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI and Society*, *35*(3), 611–623. https://doi.org/10.1007/s00146-019-00931-w

Barnhart, B. (2021). *Everything you need to know about social media algorithms*. Sprout Social. https://sproutsocial.com/insights/social-media-algorithms/

Booker, B. (2019, March 19). After lawsuits, Facebook announces changes to alleged discriminatory ad targeting. *NPR*. https://www.npr.org/2019/03/19/704831866/after-lawsuits-facebook-announces-changes-to-alleged-discriminatory-ad-targeting

Bucher, T. (2012). Want to be on the top? Algorithmic power and the threat of invisibility on Facebook. *New Media and Society*, *14*(7), 1164–1180. https://doi.org/10.1177/1461444812440159

Bucher, T. (2017). The algorithmic imaginary: Exploring the ordinary affects of Facebook algorithms. *Information Communication and Society*, *20*(1), 30–44. https://doi.org/10.1080/1369118X.2016.1154086

Cotter, K. (2019). Playing the visibility game: How digital influencers and algorithms negotiate influence on Instagram. *New Media and Society*, *21*(4), 895–913. https://doi.org/10.1177/1461444818815684

Cotter, K. (2022). Practical knowledge of algorithms: The case of BreadTube. *New Media and Society*, *0*(0), 1–20. https://doi.org/10.1177/14614448221081802

Cotter, K., & Reisdorf, B. C. (2020). Algorithmic knowledge gaps: A new dimension of (digital) inequality. *International Journal of Communication*, *14*, 745–765.

Danks, D., & London, A. J. (2017). Algorithmic bias in autonomous systems. *Proceedings of the Joint Conference on Artificial Intelligence (IJCAI)*, 1–7.

DeVito, M. A. (2021). Adaptive folk theorization as a path to algorithmic literacy on changing platforms. *Proceedings of the ACM Conference on Human-Computer Interaction*, *5*(CSCW2). https://doi.org/10.1145/3476080

DeVito, M. A. (2022). How transfeminine TikTok creators navigate the algorithmic trap of visibility via folk theorization. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW2), 380:1-380:31. https://doi.org/10.1145/3555105

DeVito, M. A., Birnholtz, J., Hancock, J. T., French, M., & Liu, S. (2018). How people form folk theories of social media feeds and what it means for how we study self-presentation.

Proceedings of the Conference on Human Factors in Computing Systems, *2018-April*, 1–12. https://doi.org/10.1145/3173574.3173694

DeVito, M. A., Gergle, D., & Birnholtz, J. (2017). "Algorithms ruin everything": #RIPTwitter, folk theories, and resistance to algorithmic change in social media. *Proceedings of the Conference on Human Factors in Computing Systems*, *2017-May*, 3163–3174. https://doi.org/10.1145/3025453.3025659

DeVos, A., Dhabalia, A., Shen, H., Holstein, K., & Eslami, M. (2022). Toward user-driven algorithm auditing: Investigating users' strategies for uncovering harmful algorithmic behavior. *CHI Conference on Human Factors in Computing Systems*, 1–19. https://doi.org/10.1145/3491102.3517441

Dienlin, T., & Metzger, M. J. (2016). An extended privacy calculus model for SNSs: Analyzing self-disclosure and self-withdrawal in a representative U.S. sample. *Journal of Computer-Mediated Communication*, *21*(5), 368–383. https://doi.org/10.1111/jcc4.12163

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2015). Algorithm aversion: People erroneously avoid algorithms after seeing them err. *Journal of Experimental Psychology: General*, *144*(1), 114–126. https://doi.org/10.1037/xge0000033

Dietvorst, B. J., Simmons, J. P., & Massey, C. (2018). Overcoming algorithm aversion: People will use imperfect algorithms if they can (even slightly) modify them. *Management Science*, *64*(3), 1155–1170. https://doi.org/10.1287/mnsc.2016.2643

Dogruel, L., Masur, P., & Joeckel, S. (2021). Development and validation of an algorithm literacy scale for Internet users. *Communication Methods and Measures*, *00*(00), 1–19. https://doi.org/10.1080/19312458.2021.1968361

Eslami, M., Karahalios, K., Sandvig, C., Vaccaro, K., Rickman, A., Hamilton, K., & Kirlik, A. (2016). First I "like" it, then I hide it: Folk theories of social feeds. *Proceedings of the Conference on Human Factors in Computing Systems*, 2371–2382. https://doi.org/10.1145/2858036.2858494

Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C. (2015). I always assumed that I wasn't really that close to [her]. *Proceedings of the ACM Conference on Human Factors in Computing Systems*, *2015-April*(January 2016), 153–162. https://doi.org/10.1145/2702123.2702556

Festic, N. (2020). Same, same, but different! Qualitative evidence on how algorithmic selection applications govern different life domains. *Regulation and Governance*, *16*, 85–101. https://doi.org/10.1111/rego.12333

Festl, R. (2021). Social media literacy & adolescent social online behavior in Germany. *Journal of Children and Media*, *15*(2), 249–271. https://doi.org/10.1080/17482798.2020.1770110

Garvie, C., & Frankle, J. (2016). Facial-Recognition Software Might Have a Racial Bias Problem. *The Atlantic*, 1–9.

Gottfried, J., & Grieco, E. (2018). *Younger Americans are better than older Americans at telling factual news statements from opinions*. Pew Research Center. https://www.pewresearch.org/fact-tank/2018/10/23/younger-americans-are-better-than-older-americans-at-telling-factual-news-statements-from-opinions/

Gran, A.-B., Booth, P., & Bucher, T. (2021). To be or not to be algorithm aware: A question of a new digital divide? *Information, Communication & Society*, *24*(12), 1779–1796. https://doi.org/10.1080/1369118X.2020.1736124

Hamilton, K., Karahalios, K., Sandvig, C., & Eslami, M. (2014). A path to understanding the effects of algorithm awareness. *Extended Abstracts on Human Factors in Computing Systems*, 631–642. https://doi.org/10.1145/2559206.2578883

Hargittai, E. (2009). An update on survey measures of web-oriented digital literacy. *Social Science Computer Review*, *27*(1), 130–137. https://doi.org/10.1177/0894439308318213

Hargittai, E., Gruber, J., Djukaric, T., Fuchs, J., & Brombach, L. (2020). Black box measures? How to study people's algorithm skills. *Information Communication and Society*, *23*(5), 764–775. https://doi.org/10.1080/1369118X.2020.1713846

Head, A. J., Fister, B., & MacMillan, M. (2020). *Information literacy in the age of algorithms: Student experiences with news and information, and the need for change*. Project Information Research Institute. https://projectinfolit.org/ publications/algorithm-study/

Horton, F. W. (1983). Information literacy vs. Computer literacy. *Bulletin of the American Society for Information Science*, *9*(4), 14–16.

Huszár, F., Ktena, S. I., O'Brien, C., Belli, L., Schlaikjer, A., & Hardt, M. (2022). Algorithmic amplification of politics on Twitter. *Proceedings of the National Academy of Sciences, 119*(1), e2025334119. https://doi.org/10.1073/pnas.2025334119

Janssen, J., Stoyanov, S., Ferrari, A., Punie, Y., Pannekeet, K., & Sloep, P. (2013). Experts' views on digital competence: Commonalities and differences. *Computers & Education, 68*, 473–481. https://doi.org/10.1016/j.compedu.2013.06.008

Johnston, B., & Webber, S. (2005). As we may think: Information literacy as a discipline for the information age. *Research Strategies*, *20*(3), 108–121. https://doi.org/10.1016/j.resstr.2006.06.005

Karizat, N., Delmonaco, D., Eslami, M., & Andalibi, N. (2021). Algorithmic folk theories and identity: How TikTok users co-produce knowledge of identity and engage in algorithmic resistance. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–44. https://doi.org/10.1145/3476046

Kirkpatrick, K. (2016). Battling algorithmic bias. *Communications of the ACM*, *59*(10), 16–17. https://doi.org/10.1145/2983270

Kitchin, R. (2017). Thinking critically about and researching algorithms. *Information Communication and Society*, *20*(1), 14–29. https://doi.org/10.1080/1369118X.2016.1154087

Klawitter, E., & Hargittai, E. (2018). "It's like learning a whole other language": The role of algorithmic skills in the curation of creative goods. *International Journal of Communication*, *12*, 3490–3510. https://doi.org/10.5167/uzh-168021

Klinger, U., & Svensson, J. (2018). The end of media logics? On algorithms and agency. *New Media & Society*, *20*(12), 4653–4670. https://doi.org/10.1177/1461444818779750

Klug, D., Qin, Y., Evans, M., & Kaufman, G. (2021). Trick and please. A mixed-method study on user assumptions about the TikTok algorithm. *ACM International Conference Proceeding Series*, 84–92. https://doi.org/10.1145/3447535.3462512

Koc, M., & Barut, E. (2016). Development and validation of New Media Literacy Scale (NMLS) for university students. *Computers in Human Behavior*, *63*, 834–843. https://doi.org/10.1016/j.chb.2016.06.035

Koenig, A. (2020). The algorithms know me and I know them: Using student journals to uncover algorithmic literacy awareness. *Computers and Composition*, *58*, 102611. https://doi.org/10.1016/j.compcom.2020.102611

Koumchatzky, N., & Andryeyev, A. (2017). *Using deep learning at scale in Twitter's Timelines*. Twitter Blog. https://blog.twitter.com/engineering/en_us/topics/insights/2017/using-deep-learning-at-scale-in-twitters-timelines

Latzer, M., & Festic, N. (2019). A guideline for understanding and measuring algorithmic governance in everyday life. *Internet Policy Review*, *8*(2), 1–19. https://doi.org/10.14763/2019.2.1415

Lee, A. Y., Mieczkowski, H., Ellison, N. B., & Hancock, J. T. (2022). The algorithmic crystal: Conceptualizing the self through algorithmic personalization on TikTok. *Proceedings of the ACM on Human-Computer Interaction*, *6*(CSCW2), 1–22. https://doi.org/10.1145/3555601

Livingstone, S. (2004). Media literacy and the challenge of new information and communication technologies. *Communication Review*, *7*(1), 3–14. https://doi.org/10.1080/10714420490280152

Logg, J. M., Minson, J. A., & Moore, D. A. (2019). Algorithm appreciation: People prefer algorithmic to human judgment. *Organizational Behavior and Human Decision Processes*, *151*(December 2018), 90–103. https://doi.org/10.1016/j.obhdp.2018.12.005

Lomborg, S., & Kapsch, P. H. (2020). Decoding algorithms. *Media, Culture and Society*, *42*(5), 745–761. https://doi.org/10.1177/0163443719855301

Ma, R., & Kou, Y. (2021). "How advertiser-friendly is my video?": YouTuber's socioeconomic interactions with algorithmic content moderation. *Proceedings of the ACM on Human-Computer Interaction*, *5*(CSCW2), 1–25. https://doi.org/10.1145/3479573

Makady, H. (2021). "I wouldn't react to it because of the algorithm": How can self-presentation moderate news consumption. *AEJMC*.

Ohme, J. (2021). Algorithmic social media use and its relationship to attitude reinforcement and issue-specific political participation – The case of the 2015 European immigration movements. *Journal of Information Technology & Politics*, *18*(1), 36–54. https://doi.org/10.1080/19331681.2020.1805085

Polanco-Levicán, K., & Salvo-Garrido, S. (2022). Understanding social media literacy: A systematic review of the concept and Its competences. *International Journal of Environmental Research and Public Health*, *19*(14). https://doi.org/10.3390/ijerph19148807

Powers, E. (2017). My News Feed is Filtered?: Awareness of news personalization among college students. *Digital Journalism*, *5*(10), 1315–1335. https://doi.org/10.1080/21670811.2017.1286943

Rader, E., Cotter, K., & Cho, J. (2018). Explanations as mechanisms for supporting algorithmic transparency. *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems*, *2018-April*, 1–13. https://doi.org/10.1145/3173574.3173677

Rader, E., & Gray, R. (2015). Understanding user beliefs about algorithmic curation in the Facebook News Feed. *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems - CHI '15*, 173–182. https://doi.org/10.1145/2702123.2702174

Rainie, L., & Anderson, J. (2017). *Code-dependent: Pros and cons of the algorithm age*. Pew Research Center. https://www.pewresearch.org/internet/2017/02/08/code-dependent-pros-and-cons-of-the-algorithm-age/

Reisdorf, B. C., & Blank, G. (2021). Algorithmic literacy and platform trust. In E. Hargittai (Ed.), *Handbook of Digital Inequality* (pp. 338–354). Edward Elgar Publishing. https://www.e-elgar.com/shop/usd/handbook-of-digital-inequality-9781788116565.html

Schwartz, S. A., & Mahnke, M. S. (2018). I – Facebook – world: How people relate to technology and the world through Facebook use. *Proceedings of the 9th International Conference on Social Media and Society - SMSociety '18*, 370–374. https://doi.org/10.1145/3217804.3217947

Seaver, N. (2019). Knowing algorithms. In J. Vertesi & D. Ribes (Eds.), *DigitalSTS: A field guide for science & technology studies* (pp. 412–422). Princeton University Press.

Siles, I., & Meléndez-Moran, A. (2021). "The most aggressive of algorithms": User awareness of and attachment to TikTok's content personalization. *Paper Presented at the 71st Annual Conference of the International Communication Association (ICA), Denver, USA*.

Siles, I., Segura-Castillo, A., Solís, R., & Sancho, M. (2020). Folk theories of algorithmic recommendations on Spotify: Enacting data assemblages in the global South. *Big Data and Society*, *7*(1). https://doi.org/10.1177/2053951720923377

Silva, D. E., Chen, C., & Zhu, Y. (2022). Facets of algorithmic literacy: Information, experience, and individual factors predict attitudes toward algorithmic systems. *New Media & Society*, 146144482210980. https://doi.org/10.1177/14614448221098042

Simpson, E., Hamann, A., & Semaan, B. (2022). How to tame "your " algorithm: LGBTQ + users ' domestication of TikTok. *Proceedings of the ACM on Human-Computer Interaction*, *6*(GROUP), 1–27. https://doi.org/10.1145/3492841

Swart, J. (2021a). Experiencing algorithms: How young people understand, feel about, and engage with algorithmic news selection on social media. *Social Media and Society*, *7*(2). https://doi.org/10.1177/20563051211008828

Swart, J. (2021b). Tactics of news literacy: How young people access, evaluate, and engage with news on social media. *New Media & Society*, 146144482110114. https://doi.org/10.1177/14614448211011447

Tech@Facebook. (2021). *How does News Feed predict what you want to see?* https://tech.fb.com/news-feed-ranking/

Thorson, K., & Wells, C. (2016). Curated flows: A framework for mapping media exposure in the digital age. *Communication Theory*, *26*(3), 309–328. https://doi.org/10.1111/comt.12087

TikTok. (2020, June 18). *How TikTok recommends videos #ForYou*. Newsroom | TikTok. https://newsroom.tiktok.com/en-us/how-tiktok-recommends-videos-for-you

Titcomb, J. (2017). Instagram is changing its feed to show photos out of order. *The Daily Telegraph*. https://www.telegraph.co.uk/technology/2016/03/16/instagram-is-changing-its-feed-to-show-photos-out-of-order/

Trepte, S., & Masur, P. K. (2020). Need for privacy. In *Encyclopedia of Personality and Individual Differences* (pp. 3132–3135). Springer International Publishing. https://doi.org/10.1007/978-3-319-24612-3_540

van Deursen, A. J. A. M., & van Dijk, J. A. G. M. (2014). The digital divide shifts to differences in usage. *New Media and Society*, *16*(3), 507–526. https://doi.org/10.1177/1461444813487959

Wallaroo Media. (2021). *Facebook News Feed algorithm history*. https://wallaroomedia.com/facebook-newsfeed-algorithm-history/

Winter, S., Metzger, M. J., & Flanagin, A. J. (2016). Selective use of news cues: A multiple-motive perspective on information selection in social media environments. *Journal of Communication*, *66*(4), 669–693. https://doi.org/10.1111/jcom.12241

Yeomans, M., Shah, A., Mullainathan, S., & Kleinberg, J. (2019). Making sense of recommendations. *Journal of Behavioral Decision Making*, *32*(4), 403–414. https://doi.org/10.1002/bdm.2118

Ytre-Arne, B., & Moe, H. (2021). Folk theories of algorithms: Understanding digital irritation. *Media, Culture and Society*, *43*(5), 807–824. https://doi.org/10.1177/0163443720972314

Zarouali, B., Boerman, S. C., & de Vreese, C. H. (2021). Is this recommended by an algorithm? The development and validation of the algorithmic media content awareness scale (AMCA-scale). *Telematics and Informatics*, *62*(February), 101607. https://doi.org/10.1016/j.tele.2021.101607