What Do We Know about Algorithmic Literacy?
The Status Quo and a Research Agenda for a Growing Field

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Abstract

The increasing emergence of algorithms in our daily use of technologies comes with a growing field of empirical research attempting to understand how knowledgeable individuals are about algorithms. This field is marked by a certain diversity in terms of how it theorizes and measures people's literacy when interacting with algorithms. We propose converging on the term *algorithmic literacy* that covers different dimensions used by previous research. This article summarizes the state of knowledge on algorithmic literacy. Drawing on this, we propose an agenda including five different directions that future research could focus on: 1) theory building to understand algorithmic literacy, 2) addressing the algorithmic divide, 3) uncovering the relationship between algorithmic literacy and attitudes, 4) examining algorithmic literacy as predictor for user behavior, and 5) exploring ways to increase algorithmic literacy.

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

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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 available post inventory and 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 we are and how connected we are to others in our network based on the content we are presented. Yet, the exact algorithmic formulas for these and other social media platforms 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 this may be influencing how informed they are. 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 and in light of technological advancement, 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” (Fest, 2021) to describe

people's cognitive, technical, motoric and emotional abilities required 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 algorithms filtering information that is processed and displayed through new technologies. Works addressing this very specific form of digital literacy initially showed that while algorithmic awareness (i.e., knowing about the existence of algorithms) is generally increasing (e.g., Klawitter & Hargittai, 2018), those without this knowledge may be disadvantaged by missing out on important information that is not prioritized for them (Rainie & Anderson, 2017). Closely related, the concept of "algorithmic literacy" – being aware of the presence and the impact of algorithm-based systems and knowing how to use this understanding (DeVito, 2021) – has been deemed the next digital divide (Gran et al., 2021), as those with lower education and less experience with online tools show more limited algorithmic knowledge (Cotter & Reisdorf, 2020). Therefore, it seems that the prevalence of a very specific form of digital literacy, that is, algorithmic literacy, also follows the principles described in the well-established digital inequality framework (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 also unknown 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,

a wiki, 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 actually 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.

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 are the evolution of years of varied concepts of algorithmic understanding, and attempt to incorporate many sub-dimensions. The first proposes two stages of understanding, from mere awareness to practical use, while the second expands literacy to four steps, by distinguishing awareness from knowing, and adding in the ability to critique algorithms. While these definitions offer necessarily nuanced definitions of literacy, they propose different levels of granularity in terms of what constitutes “literacy” comprehensively.

The term *algorithmic literacy* is the latest iteration of algorithmic understanding, built on several prior concepts around algorithmic understanding which vary in breadth and depth. First came 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 use the term *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).

Even *algorithmic literacy*, as a collective term, is multi-faceted. Swart (2021) 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.

The levels of algorithmic literacy (i.e., awareness, knowledge, skills) fit into these dimensions. Dogruel, et al. (2021) categorize *awareness* and *knowledge* as cognitive dimensions of understanding algorithms. While representing distinct levels of understanding, neither necessarily extends to affective or behavioral aspects. Building on this, Cotter (2022) taps into the behavioral by proposing the *practical knowledge* of algorithms, “to capture knowledge located at the intersection of practice and discourse” (p. 2). Thus, “knowing” extends beyond knowing the factual basis for knowing *that* an algorithm exists to making sense of *how* it is used in practice. This borders on the use of *skills*, 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, affective understanding 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 at least 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 literacy, information literacy, Internet literacy, digital literacy, social media literacy), are also multi-faceted, incorporating elements of their previous literacies. For instance, a recent systematic review of social media literacy as a concept (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 the boundaries between them. Moving forward, this allows the development of literacy frameworks, which can

address literacy gaps and lead to the development literacy interventions along the lines of previous literacy research in communication technology.

The Evolving Algorithmic Literacy of Social Media Users

Research on the broad concept of algorithmic literacy does not have a definitive start, but within the context of social media it can at least be traced back to the implementation of the algorithms themselves. 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).

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, though this work did not involve users directly. Initial empirical work on Facebook users' experiences with algorithms showed that the majority (62.5%) were 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). Yet, when asked more openly whether they thought Facebook always showed all their friends' posts, the majority (73%) said no (Rader & Gray, 2015), even if they did not understand how such filtering worked, or why it was done. Continued research shows that awareness of algorithms is growing rapidly. For instance, most online news users now realize that content must somehow be filtered, but still

have a limited understanding of the criteria used for such filtering (Powers, 2017; Swart, 2021). 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). Notably, TikTok users are 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).

Yet, even those actively invested in understanding algorithms can only glean so much from their interactions with them. From a business perspective, 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 and social media posting 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 those seeking community, 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, Hamann, & Semaan, 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 facing the consequences.

Folk Theories

When faced with the growing recognition of algorithms, but limited available knowledge about how they work, users began developing 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). Through their use of social media, individuals develop an *algorithmic imaginary*, the “way in which people imagine, perceive and experience algorithms and what these imaginations make possible” (p. 31). For instance, Facebook users developed four main theories about algorithms in their feeds, based on their experiences (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. About one-third of users also believed in a *global popularity* theory that content was more likely to show up in their feed if it had received more likes. Remaining folk theories by some users were the *format theory*, which stated that posts with media content get higher algorithmic priority, and the *narcissus theory*, which posited that users are likely to see content from those who are similar to themselves (cf. Dogruel, 2021, for similar results).

Algorithmic folk theories are both general and platform-specific. Research on Spotify folk theories (Siles et al., 2020) reveals 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 make it

to other users' video feeds, and assumed it was a combination of video engagement, posting time, and using the right hashtags (Klug et al., 2021).

How do users come to develop folk theories? DeVito et al. (2018) explored what sources of information Facebook users rely on to build their folk theories about the platform. The vast majority build on *endogenous information*, or their own experiences within the platform, such as patterns of who and what appears in their feeds. *Exogenous information* from other media or discussions with friends was also used, and opinions from those close to them were particularly important. For most users, these folk theories are malleable, adapting to accommodate algorithmic changes on the platforms (DeVito, 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., Broadband Internet access in the U.S.). 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, Fister, & MacMillan, 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 the vast majority of online content that users engage with controlled by algorithms, a lack of information literacy implies a lack of algorithmic literacy, with even greater detrimental informational 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 that user to believe that the limited political information they are seeing in their feeds is the whole and accurate political reality around, which only further fueling echo chambers of disinformation.

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 based on normative and stereotypical narratives, in a process called *algorithmic symbolic annihilation* (Andalibi & Garcia, 2021). For instance, individuals who have experienced pregnancy loss continue to be subjected to content about pregnancy that does not account for their experience.

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 can become biased through many earlier steps, starting with when they learn from input data that is already biased. 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). In the social media space, this could mean dominant groups receiving target ads for 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: awareness, profiling transparency, management, control, and selective memory. *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 intervention points 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 interventions conditions that would improve algorithmic skills. Finally, selective memory might be the result of clearer profiling, management, and control that influences key attitudes about algorithms such as appreciation or aversion, and thus their continued use.

Investigating Algorithmic Literacy

As Kitchin (2017) notes, researching users' understanding of algorithms is challenging because to start, 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 we could know one, it may not usefully inform us of another. Third, algorithms are by their design dynamic, learning from user data to constantly improve their output, so any insight into the current formula is 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 have been diverse, ranging from focus groups (Siles et al., 2020) to surveys (Cotter & Reisdorf, 2020) to computational approaches (DeVito et al., 2017). Naturally, each method offers a unique lens for assessing algorithmic literacy, while also presenting limitations. Whereas strengths and weaknesses exist for methods in all social scientific research, 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.

Research in this space began by investigating algorithmic experiences through qualitative methods such as in-depth interviews. Particularly in uncovering folk theories, qualitative studies about Facebook (Bucher, 2017), Google News (Powers, 2017), YouTube (Alvarado et al., 2020), Spotify (Siles et al., 2020), and TikTok (Klug et al., 2021) asked users to share their experiences with these platforms. 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. Yet, this limits the ability to draw broader common inferences about an algorithmic experience.

The move by some studies to quantitative surveys allows for correlation, prediction, and comparison between algorithmic literacy and other concepts across users missing from qualitative methods, but their unified measures sacrifice some of the unique experiences each user would have with algorithms that learn from their very engagement. 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.

As the research builds on a foundation of qualitative data to develop quantitative assessments, it distills the rich experiences of engaging algorithms into replicable but uniform measures. This highlights a current tension in algorithmic literacy research between capturing the individual nuance of algorithmic experiences and offering generalizability about them. What is largely still missing is experimental tests of the effects of algorithmic literacy on various cognitive, affective, or behavioral outcomes in social media use, although the most recent research has started testing the effects of exposure to algorithmic information on attitudes (Silva et al., 2022). Thus, we propose assessing how algorithmic literacy predicts cognitive or behavioral processes as the next important step in understanding the role of algorithmic literacy in social media use.

Measuring Algorithmic Literacy

Dogrue, 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). While this scale takes a useful step forward in assessing literacy, it ultimately still breaks into two sub-scales that together do not clearly 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, 2021). 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 (Koenig, 2020; e.g., 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 the most 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 research 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.

Zarouali, et al. (2021) validated their algorithmic awareness scale against a measure of algorithmic knowledge, comprised in their study of true/false statements about common algorithmic misconceptions. They find algorithmic awareness and algorithmic knowledge to be positively correlated, but distinct concepts. Yet, Cotter and Reisdorf's (2020) measure of algorithmic knowledge differs from Zarouali et al.'s, consisting of a scale asking participants to rank how much influence they feel various actions, such as their geographic location and their past search history, have on their search engine results. Like awareness, measures of knowledge may look different across platforms. Therefore, rather than focusing on distinguishing these two separate concepts, or simply combining them in one scale, future research should focus on further developing overall measures of algorithmic literacy for social media and testing what sub-factors are supported empirically.

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: algorithmic literacy 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 , as well as c) as a dependent variable by asking how it can be changed.

Taking these three roles into account, we propose a research agenda intended to extend our theoretical and empirical knowledge about algorithmic literacy as a key variable in today's use of contemporary technologies.

Understanding Algorithmic Literacy: A Call for Theory Building

We believe that – as one of the main purposes of research – the omnipresence of algorithms in social media users' daily lives require communication scholars to build a theoretical framework. What could a theory on algorithmic literacy look like? Following the idea of human-algorithm-interaction Lomborg and Kapsch (2020), we argue that theory needs to represent both entities – the human and the algorithm – and describe how their interaction can shape algorithmic literacy as a dependent variable. More specifically, a theoretical framework could specify both what users need to understand, and which technological cues or properties are accessible to users to support this understanding. For example, Rader, Cotter, and Cho (2018) test short explanatory statements that reveal key elements of the Facebook algorithm to its users, including what, how, and why information ends up in their feeds. Some apps also 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.

Likewise, a theory-driven approach on algorithmic literacy could draw on the Algorithmic Experience framework (Alvarado & Waern, 2018) and outline which psychological processes operate when individuals interact with each of these technological cues and properties.

Besides identifying these processes, a theoretical 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 could also include key variables that significantly shape the level of algorithmic literacy besides the actual human-algorithm-interaction such as age or technological experience.

Such an attempt of theoretical advancement could be informed by the knowledge gathered in the context of algorithmic folk theories but also by the different concepts that aim to represent algorithmic literacy. 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, Mieczkowski, Ellison, & Hancock, 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 and behavioral responses reflecting a certain level of algorithmic literacy. This kind of theorizing would help to build a platform-agnostic understanding of algorithmic literacy in a sustainable form. The greatest challenge that requires comprehensive exploration is the theoretical definition of technological cues that signal the presence of algorithms. While algorithmic literacy has already conceptualized as dependent variable by studies targeting at socio-demographic determinants (see below), modeling situational and technological factors that change algorithmic literacy will provide practical implications to design further interventions.

Addressing the Algorithmic Divide

First, a 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, Delmonaco, Eslami, & Andalibi, 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.

Uncovering the Relationship between Algorithmic Literacy and Attitudes

As revealed by previous research, users' willingness to use algorithms and interact with them is significantly dependent on the appraisal thereof and their functioning. This line of research modeled algorithmic literacy as predictor of evaluations and actions and suggested that

the relationship between algorithmic literacy and attitudes is more complex than just a linear association. The idea that that the more knowledge people have about algorithms the more positive attitudes they hold toward them received limited empirical corroboration (Araujo et al., 2020; Dietvorst et al., 2015; Yeomans et al., 2019). Instead, it seems plausible to assume that this relationship depends on users' needs and motivations in the face of the functionalities of algorithms. Indeed, initial evidence indicated 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).

Recent research has begun to test algorithmic literacy interventions, but finds that even exposing users to more information about algorithms does little to change their attitudes, without accounting for technological power usage (Silva et al., 2022). Following this line of thought, it is key to analyze users' individual differences that could intervene in the relationship between algorithmic literacy 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). Thus, the interplay of motivation, literacy, and attitudes seems to be a promising path to address a differential view on how users evaluate certain algorithms and why.

Examining Algorithmic Literacy as a Predictor for User Behavior

Technological literacy has long been treated as key qualification for responsible and desirable user behavior in human-technology interaction (Livingstone, 2004). Analogously, one could expect that higher individual literacy concerning algorithms goes hand in hand with a precautionary use of algorithms. Still, it is normatively difficult to estimate which behaviors are

desirable: users feeding the algorithm with more information so that it becomes more accurate, or users refraining from disclosing information to protect their privacy. Again, the desirability of a behavior might be a function of users' individual needs (for instance, their need for privacy; Trepte & Masur, 2020). Besides varying levels of needs among users, it seems that users' communicative actions on social media do not follow linear trajectories (in the sense of the more they know, the more they protect their information) but instead a more complex calculus of what they gain versus what they lose when disclosing certain types of information (Dienlin & Metzger, 2016). This is certainly applicable to the context of algorithms: If users reach a certain level of algorithmic literacy, they might have a greater ability to estimate the risks and the benefits of feeding this algorithm.

This calculus has not only implications 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). The key question seems here: In which situations do the risks of an algorithmic curation outweigh the benefits through users' subjective lenses? And to what extent is this calculus observable for users with low levels of algorithmic literacy? 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.

Exploring Ways to Increase Algorithmic Literacy

From a normative and practical point of view, it seems commendable to investigate the previous points to develop and customize interventions that help users to increase their algorithmic literacy as a dependent variable. Especially in face of potential behavioral calculus, 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 previous empirical work, we could take several approaches to designing interventions that increase algorithmic literacy. Though current knowledge about what predicts such literacy is slim, exploration could start with the rich user experience pulled from folk theories, attitudes, and users' own attempts to learn about algorithms. Four key psychological concepts from this research seem particularly important to consider: curiosity, motivation, control, and practice. These reflect personality, situational, attitudinal, and behavioral aspects.

First, it seems important to trigger curiosity about algorithms. While the vast majority of social media users are now aware 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 in order to learn more. 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.

Second, motivation to engage with algorithms seems crucial. Passive social media users may not be particularly motivated to understand 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 strategies 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. 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.

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 users' 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). 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. This would directly teach users about some aspects of the algorithm, and could potentially motivate them to learn more.

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.

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 and behavioral outcomes, and how to improve it. Thus, we present an agenda for moving forward with algorithmic literacy research, which includes addressing the algorithmic divide, mapping the link between literacy and attitudes, and understanding influences in user behavior.

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