International Journal of Communication 14(2020), 745–765 1932–8036/20200005

Algorithmic Knowledge Gaps: A New Dimension of (Digital) Inequality

KELLEY COTTER[1]
Michigan State University, USA

BIANCA C. REISDORF
University of North Carolina at Charlotte, USA

Algorithms serve as gatekeepers and arbiters of truth online. Understanding how algorithms influence which information individuals encounter better enables them to properly calibrate their reception of the information. Yet, knowledge of platform algorithms appears to be limited and not universally distributed. In line with the long history of knowledge inequities, we suggest that algorithmic knowledge varies according to socioeconomic advantage. We further argue that algorithms are *experience technologies* in that they are more easily understood through use. Nevertheless, socioeconomic background continues to shape information and communication technology use, thereby further influencing disparities in algorithmic knowledge. Using data from a survey of a random sample of Internet users in the United States, we found support for the relationship between algorithmic knowledge and socioeconomic background in the context of online search. The findings provide preliminary evidence that extant structural inequalities underlie algorithmic knowledge gaps in this domain.

Keywords: algorithms, algorithmic knowledge, algorithmic literacy, knowledge gaps, digital divides, digital inequality, digital literacy

As algorithms have become increasingly involved in processes of information organization, seeking, and acquisition online, some have raised concerns over their ability to influence the way we conceive of ourselves and the world around us (Beer, 2009; Cheney-Lippold, 2011; Gillespie, 2014; Kitchin & Dodge, 2011). Algorithms rest on ontological decisions made by developers who "place a particular philosophical frame on the world that renders it amenable to the work of code and algorithms" (Kitchin & Dodge, 2011, p. 247). In the context of information acquisition, algorithms make decisions that ultimately define the scope

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Kelley Cotter: cotterk6@msu.edu
Bianca C. Reisdorf: breisdor@uncc.edu
Date submitted: 2019–06–26

[1] We wish to thank the anonymous reviewers for their helpful comments. We would also like to extend our gratitude to Bill Dutton for his comments on a version of this article. We wish to acknowledge Google, Inc., for supporting this research. As agreed with Google, representatives of the company had not seen or approved this article prior to publication.

of human knowledge and means of knowing (Gillespie, 2014). Yet, the principles on which such decisions arise nearly always remain obscured. Algorithmic platforms, such as search engines and social media, convey information according to extant dominant social, cultural, political, and commercial logics (Gillespie, 2014; Noble, 2018). Yet, in many cases, users are not aware of the role that algorithms play in mediating information (Eslami et al., 2015; Rader, Cotter, & Cho, 2018; Rader & Gray, 2015), let alone the implications thereof. Without such knowledge, users may believe that the information they encounter objectively represents the most trustworthy, authoritative, and relevant information. Consequently, knowledge built on the foundation of algorithmic platforms may uncritically reflect the dominant discourses inscribed in the underlying code.

Although algorithms have increasingly surfaced in public discourse in recent years, it is not certain that knowledge of how algorithms work is universally shared. Some early work has suggested that "algorithmic skills remain the domain of a select few users" (Klawitter & Hargittai, 2018, p. 3505). This article examines potential inequities in what people know about algorithms in the context of online search. Such inequities may compound existing epistemic power by reifying the assumptions, principles, and commitments on which algorithms are built via knowledge building and production. We focus on online search because of its centrality in contemporary information seeking and acquisition, processes that lay the foundation for knowledge building and production. We propose that patterns of algorithmic knowledge building reflect the long history of information inequities throughout human history, which correspond to socioeconomic advantage (Lievrouw & Farb, 2005). To support this argument, we draw on research on knowledge gaps, digital divides, and inequality, and the nascent body of work exploring algorithmic knowledge building to propose and test predictors of algorithmic knowledge that reflect structural distributions of resources.

The knowledge gap hypothesis argues that segments of the population with greater socioeconomic advantages acquire information typically distributed via mass media at a faster rate than others (Tichenor, Donohue, & Olien, 1970). This uneven acquisition of information occurs because of socialization and stratification processes, whereby those with more resources experience greater opportunities for encountering, attending to, and retaining information more than others (Tichenor et al., 1970). Whereas it is expected that individuals may acquire knowledge of algorithms via information originating in media coverage, algorithmic knowledge building slightly differs from the kind of knowledge acquisition addressed by the knowledge gap hypothesis. Topics and issues covered in the news—and addressed by knowledge gap research—are not always personally experienced or directly observable by an individual; thus, such knowledge of public affairs depends on the infusion of information in a social system, particularly as supported by media institutions (Tichenor et al., 1970). By contrast, individuals can, and do, directly interact with algorithms. The embeddedness of algorithms in online processes results in individuals routinely interacting with algorithms throughout their everyday practices (Willson, 2017). Moreover, the complexity of algorithms (Ananny & Crawford, 2016; Burrell, 2016) and efforts by platform owners to conceal details about them (Pasquale, 2015) mean that information about algorithms disseminated via news coverage is limited. However, recent work has evidenced that the presence of algorithms on online platforms and what they do is (partially) discernible by users directly through interaction and observation. Indeed, much of what individuals know about algorithms originates from experiences with them, which alert individuals to the algorithmic processes and provide clues about algorithms' operational logics (DeVito, Birnholtz, Hancock, French, & Liu, 2018; Eslami et al., 2015; Rader & Gray, 2015). In this way, platform algorithms can be considered *experience technologies* (Blank & Dutton, 2012; Dutton & Shepherd, 2006) in which use of an algorithmic platform permits users to learn about how a specific algorithm works. Still, the digital divide and inequality literature has consistently demonstrated that social and economic constraints stifle physical access to and use of information and communication technologies (ICTs). More advantaged individuals are able to exercise greater autonomy in their use of ICTs, resulting in more frequent and extensive use (Blank & Groselj, 2014; DiMaggio, Hargittai, Celeste, & Shafer, 2004; Robinson, 2009; Zillien & Hargittai, 2009). Consequently, these individuals may also experience greater opportunities for learning about platform algorithms through their experiences with them.

Algorithmic Knowledge

What Is Algorithmic Knowledge?

What can be known about algorithms in practice is notoriously contentious (Ananny & Crawford, 2016; Bucher, 2018). Efforts by platform owners to conceal or obscure details about their algorithms as part of corporate secrecy make it difficult to know for certain how and why algorithms produce particular outputs or outcomes (Pasquale, 2015). Yet, even with full transparency, other characteristics of algorithms further constrain knowledge. Algorithms "in the wild" tend to be highly complex, bringing together a great number of variables and computational techniques, which make it difficult to grasp what they are doing and how (Burrell, 2016). Algorithms are also constantly evolving. Machine learning algorithms, in particular, evolve by definition as they encounter new data. Furthermore, the iterative design of algorithms and A/B testing of different iterations mean that to some extent algorithms "never take durable, observable forms" (Ananny & Crawford, 2016, p. 9).

Despite these constraints on developing certain knowledge, algorithms remain knowable to some extent (Bucher, 2018). Moreover, similar to digital skills generally (van Deursen & van Dijk, 2010), algorithmic knowledge likely entails sequential tiers of insight. The algorithms we focus on in this study are those that decide how to arrange webpages in search results, thereby rendering some information more prominent than other information. Processes of so-called algorithmic curation are meant to support users in navigating the deluge of information online. In this context, in its most basic form, algorithmic knowledge constitutes mere awareness that search results do not display all information sources equally and that certain information is prioritized (Eslami et al., 2015; Rader et al., 2018; Rader & Gray, 2015). Basic awareness provides a foundation on which to build an understanding of the criteria by which algorithms rank content (DeVito et al., 2018; DeVito, Gergle, & Birnholtz, 2017). 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 (Rieder, 2017).

In this study, we are interested in what Internet users do or do not know about how algorithms work in the context of search engines. In focusing on search engines, we consider the implications that algorithmic knowledge may have for subsequent knowledge building and production. Importantly, we assess algorithmic knowledge that can be verified against objective details shared about prominent search algorithms. Given these considerations, we focus our attention on knowledge that provides individuals with crucial insight about why and how certain information is prioritized in their online search results. Specifically, we focus on awareness of common factors that algorithms use to select and organize information in search results, for example, users' past search history, geographic location, search optimization, and popularity of content (Google, n.d.).

Why Algorithmic Knowledge Matters

As algorithms have gained ubiquity in contemporary media environments, many have raised concerns about their role in controlling flows of information. Algorithms play a gatekeeping role similar to news editors by intervening in the visibility of information (Gillespie, 2014). In making determinations about how algorithms can best curate information, engineers write rules that algorithms follow, for example, in calculating how relevant, important, and/or meaningful content will be to individual users, as well as how credible. These rules rest on various assumptions about the world that necessarily reflect the worldviews of those designing algorithms, a population lacking in diversity and primarily comprising those from privileged groups (Beer, 2009; Noble, 2018). These assumptions materialize in ontological processes of defining and categorizing relevant variables within data, specifying relationships between categories, and determining how algorithms will make use of the categories (Cheney-Lippold, 2011; Gillespie, 2014). Although code emerges from within a power structure, it does not always account for structural inequalities, which means that algorithms may not be alert to systemic biases embedded in data nor do they necessarily act in ways that correct them. Consequently, algorithms commonly reify hegemonic ideals and biases via the information they serve and to whom they serve it (Eubanks, 2017; Noble, 2018).

Platform algorithms also act as arbiters of truth (Gillespie, 2014). Although platforms such as Google are positioned as points of access to all there is to know, the algorithms they rely on selectively establish a realm of consequential knowledge by judging the relative value, significance, and trustworthiness of information (Gillespie, 2014). Without knowledge of algorithms, individuals lack important context that could be mobilized in assessing the merit of information they encounter on platforms. Previous studies have also demonstrated users' uncritical trust in algorithmic ranking of search results (Pan et al., 2007). Even when search results are less relevant, users tend to click higher ranked webpages (Pan et al., 2007). The ranking of websites also has a positive relationship with the perceived credibility of website owners and an indirect relationship with perceived message credibility (Westerwick, 2013). Some evidence suggests a relationship between a lack of algorithmic knowledge and inaccurate assumptions about the credibility of search results (Hargittai, Fullerton, Menchen-Trevino, & Thomas, 2010). Advertising targeting and optimization techniques can further problematize these misunderstandings of algorithmic ranking when they permit biased or false information to rise to the top of search results and social media feeds.

Putting this all together, the underlying point concerns individual autonomy. Without knowledge of algorithmic curation, users lack crucial insight into the various factors influencing who and what reaches them in search results and social media feeds. The absence of this insight undermines an individual's ability to make rational judgments about the information they encounter. Instead, a lack of algorithmic knowledge renders individuals unknowingly reliant on these algorithms for "provid[ing] a means to know what there is to know and how to know it" (Gillespie, 2014, p. 167). This lack of knowledge denies individuals the ability to properly calibrate their reception of information and act on it accordingly. Consequently, disparities in algorithmic knowledge create classes of users with the skills to question and critique algorithmic representations of reality and classes more likely to unwittingly internalize the normative discourses inscribed in algorithmic outputs (e.g., search results).

How People Build Algorithmic Knowledge

At present, little research addresses knowledge-building processes around algorithms. Most of the existing work in this area focuses on social media algorithms. Although ranking algorithms differ across platforms, they also share many commonalities (van Dijck, 2013), for example, the goal of connecting users with other people and content relevant and meaningful to them. Different ranking algorithms also use many of the same signals of relevance and meaningfulness, such as geographic location and past browsing behavior. Thus, previous findings on algorithmic knowledge not specific to online search can be informative for the present study.

Previous research suggests both “exogenous” and “endogenous” sources of insight about the operational logics of algorithms (DeVito et al., 2018). The former refers to insight gleaned from sources beyond the platform (DeVito et al., 2018). Exogenous learning is not unique to algorithms and is closely related to socioeconomic background. Primarily, learning from exogenous sources occurs through reading media reports that mention algorithms (Cotter, 2019; DeVito et al., 2018) and via interpersonal exchanges of information (Bishop, 2019; Cotter, 2019; DeVito et al., 2018). Similarly, comparing notes about what people see in their respective news feeds can alert them to differences or absences, which evidence algorithmic curation (Rader & Gray, 2015). Importantly, with exogenous learning, certain individuals—for example, content creators and marketers, whose livelihood depends on managing online visibility—are more motivated to proactively seek information about platform algorithms than others (Cotter, 2019). Similarly, those whose jobs involve computer programming likely know more about algorithms than others because of professional training and experience.

Because companies typically share few details about their algorithms, existing research generally suggests that most learning about platform algorithms occurs endogenously, that is, by acquiring insight about algorithms through direct experiences with them (DeVito et al., 2018). In this way, platform algorithms can be considered experience technologies, or technologies that are not easily understood without using them firsthand (Blank & Dutton, 2012; Dutton & Shepherd, 2006). Although individuals may learn about experience technologies in multiple ways, extensive use of these technologies drives insight by enabling individuals to accumulate observations about a technology’s pattern of behavior and to reflect on these observations over time (Blank & Dutton, 2012; Dutton & Shepherd, 2006).

Recent qualitative research on algorithmic knowledge among social media users suggests a pattern of experiential learning. As users interact with algorithmic platforms, they reflect on their observations and intuitively form beliefs about how algorithms work (DeVito et al., 2018; Rader & Gray, 2015). In support of this point, more frequent use of Facebook relates to greater awareness of the site’s news feed ranking algorithm (Eslami et al., 2015). Furthermore, previous work demonstrates that discerning connections between one’s behavior and content served can prompt awareness of algorithmic processes (DeVito et al., 2018). Similarly, noticing inconsistent or unexpected content also corresponds to greater awareness of algorithmic processes (DeVito et al., 2017; Rader & Gray, 2015). Certain motivated users, such as online entrepreneurs and content creators, learn about algorithms more proactively by experimentally varying their practices, as well as observing the practices of other more visible users (Cotter, 2019; Klawitter & Hargittai, 2018).

In short, although existing research evidences multiple pathways to knowledge, studies suggest that most users develop insight about algorithms through their use of platforms. Moreover, accumulating a variety of experiences with algorithmic platforms affords a multiplicity of opportunities and lines of sight for learning about different elements of algorithms' operational logics. For example, using a search engine to look up a fact, review news updates on a recent event, and navigate quickly to a website all illuminate different aspects of algorithmic ranking that may lead to greater overall insight. This is consistent with research on experience technologies, which maintains that a broader range of engagement with technologies helps users learn about them (Blank & Dutton, 2012; Dutton & Shepherd, 2006).

The Structural Roots of Inequities in Algorithmic Knowledge

Knowledge inequities are not new. Disparities in processes of constructing, distributing, and using information are rife throughout human history (Lievrouw & Farb, 2005). Knowledge gap research offers a well-established explanation for such disparities that underscores the role of social structures. Focusing primarily on the dissemination of information via mass media systems, the knowledge gap hypothesis contends that the rate of diffusion of information within a population varies according to socioeconomic status (SES; Gaziano, 1983; Tichenor et al., 1970). Higher SES populations tend to exhibit greater knowledge of various public affairs issues than lower SES populations (Tichenor et al., 1970). Furthermore, knowledge gaps and distribution of resources seem to be mutually constituted to some extent. SES-based knowledge gaps play a fundamental role in compounding uneven distributions of power, which further undermine levels of social influence among those with fewer socioeconomic advantages (Hwang & Jeong, 2009; Viswanath & Finnegan, 1996). Although some have suggested "ceiling effects" in which higher SES populations reach an upper limit of knowledge that allows lower SES populations to "catch up" and close gaps, this has not been widely supported in empirical studies (Viswanath & Finnegan, 1996). Instead, knowledge gaps tend to persist even as overall knowledge across a population increases: "Those who know more will continue to know more" (Viswanath & Finnegan, 1996, p. 211).

In the late 1990s, the digital revolution renewed interest in knowledge and information disparities, particularly focusing attention on the potential for ICTs to exacerbate existing inequities (Lievrouw & Farb, 2005). Research on digital divides and inequality has built on knowledge gaps research, producing valuable insight into the ways that socioeconomic advantage impacts what users know about ICTs. To further understand what factors contribute to the cultivation of algorithmic knowledge, we can treat this skill domain as a subset of a broader array of digital skills and look to digital divides and inequality research. Like knowledge gaps research, this work has consistently documented the uneven development of digital skills according to socioeconomic background: Those with more resources tend to exhibit greater skills (e.g., Hargittai & Hinnant, 2008; J. A. G. M. van Dijk, 2005; J. A. G. M. van Dijk & van Deursen, 2014).

Research on knowledge gaps and digital divides theorizes a variety of causes for unequal distributions of knowledge. The knowledge gap hypothesis argues that those able to attain higher education will be better equipped with communication and comprehension skills needed for processing information, particularly complex information (Gaziano, 1983; Tichenor et al., 1970). Moreover, prior knowledge of a topic is thought to provide a more solid analytical foundation on which individuals can build further knowledge as they encounter new information (Tichenor et al., 1970). Those with fewer resources face spatial and temporal constraints on material access to and use of ICTs, which inhibits opportunities to develop technical insight through exploratory use (Robinson, 2009). More advantaged individuals additionally benefit from formal educational environments with higher quality instruction and computer and Internet access, which better facilitate digital skill building (J. A. G. M. van Dijk, 2005; Warschauer, 2004).

Learning does not only occur within the classroom: Informal learning experiences play an important role in cultivating new knowledge, particularly digital skills (J. A. G. M. van Dijk, 2005; Warschauer, 2004). Yet, informal learning depends on the degree of social support and social capital available to individuals (Lievrouw & Farb, 2005; J. A. G. M. van Dijk, 2005; Warschauer, 2004). Higher SES individuals tend to be exposed to a broader and more diverse social sphere that provides more opportunities for encountering relevant information and discussing it with others (Tichenor et al., 1970). Moreover, those with greater resources are likely to be surrounded by friends, family, and coworkers with technical expertise to assist in learning (DiMaggio et al., 2004; J. A. G. M. van Dijk & van Deursen, 2014). In addition, more advantaged individuals are more likely to be employed and hold positions that require significant computer and Internet use as well as the development of digital skills (J. A. G. M. van Dijk, 2005). These individuals tend to benefit from "double access": access to ICTs at home and at work (J. A. G. M. van Dijk, 2005).

Social and cultural context also matter in knowledge building as it shapes people's orientation toward information (Robinson, 2009). The value of information for different communities depends on its capacity to address the realities of their lived experiences. As Lievrouw and Farb (2005) argue, "Information resources are valuable only insofar as they are meaningful or useful to the people who have access to them" (p. 514). If media reporting frames the significance of algorithms through the lens of dominant cultural discourses (T. A. van Dijk, 1995), the information may not resonate with those on the margins who may have different priorities. Consequently, those with fewer social advantages may feel less inclined to attend to media reporting about algorithms when it appears to offer little immediate value or utility. Relatedly, coverage of algorithms may vary across different media channels and outlets, which may correlate with SES-based patterns of media use (Tichenor et al., 1970). As such, more than a rupture of information access, knowledge gaps may also emerge from incongruities in the orientations and interests of those producing mainstream media coverage of algorithms and those of less advantaged media consumers.

In sum, knowledge disparities—particularly within the digital realm—are closely related to structural inequities. Those better positioned in society tend to reap the benefits of more extensive and better quality education for establishing background knowledge, autonomy of access to digital technologies that affords more ample time for developing digital skills, more diverse social ties with pertinent technical insight to share, and more receptive dispositions toward relevant media reporting.

These factors better equip those with greater socioeconomic advantages with the foundational knowledge, resources, and opportunities needed for acquiring and making sense of information about algorithms. Therefore, we expected that algorithmic knowledge would be unevenly distributed according to socioeconomic background.

H1: Socioeconomic background will relate to knowledge of algorithms.

As previously noted, much of algorithmic knowledge building occurs through experience. Thus, if individuals make use of algorithmic platforms at equal levels across a population, we should expect smaller knowledge gaps. Yet, as digital divides and inequality research has consistently shown, experience with ICTs is not equally afforded to all. Digital divides research began with a binary distinction between "haves" and "have nots" in terms of physical access (National Telecommunications and Information Administration, 1995), but as Internet penetration rates have increased, enduring disparities in the use of and skills related to ICTs suggest a second-level digital divide (Hargittai, 2002; Hargittai & Hinnant, 2008; Wei & Hindman, 2011). Socioeconomic background continues to affect how and to what extent individuals use ICTs, as well as how effectively they use them. Positive dispositions toward ICTs are contingent on the possession of a range of resources, including material resources; time; social support and use among social network ties; mental and cognitive resources; emotional resources, including self-confidence or a particular self-image that may not harmonize with using ICTs; and/or a lack cultural predilection (J. A. G. M. van Dijk, 2005). Likewise, social- and economic-related constraints on access to and use of ICTs—for example, time and proximity—can lead to negative emotional experiences with ICTs, which discourage future use (Robinson, 2009). In general, age, gender, race, education, and income all play a role in ICT access, skills, use, participation, and outcomes (e.g., Hargittai & Jennrich, 2016; Helsper & Reisdorf, 2017; Hunsaker & Hargittai, 2018; Robinson et al., 2015; van Deursen & Helsper, 2015, 2018). Studies addressing information-seeking behavior as an outcome of Internet experience have similarly implicated socioeconomic factors as predictors (e.g., Büchi, Just, & Latzer, 2016; van Deursen & van Dijk, 2014). The same findings have been reported in relation to specific types of information, such as health information (e.g., Jacobs, Amuta, & Jeon, 2017; Nguyen, Mosadeghi, & Almario, 2017) and political information (Dutton, Reisdorf, Dubois, & Blank, 2017).

In light of these patterns, we suggest that socioeconomic background drives the degree and range of experiences with algorithmic online search; as previously argued, degree and range of experiences with online search provide a principle pathway to algorithmic knowledge. Thus, we expected inequities in experiences with online search to partially shape algorithmic knowledge gaps (see Figure 1).

H2: Socioeconomic background will relate to frequency of using online search.

H3: Socioeconomic background will relate to breadth of using online search.

H4: Frequency of using online search will positively relate to knowledge of algorithms.

H5: Breadth of using online search will positively relate to knowledge of algorithms, even when controlling for frequency of using online search.

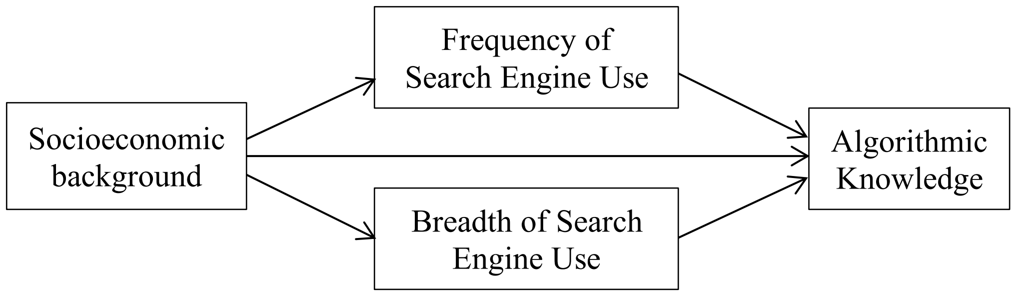

Figure 1. Impact of socioeconomic background and experience on algorithmic knowledge.

Method

Data

To examine the issues above, we used data from an online survey of a stratified random probability sample of Internet users in the United States. The U.S. data set is part of a larger study on how Internet users obtain information on politics and other topics (Dutton et al., 2017). The data were collected through a Web-based survey during January 2017. The 30-minute survey included a wide range of questions on Internet use, use of search engines, information-seeking behaviors, and demographic factors. The data set was weighted according to known population proportions, making the data fully representative of the U.S. online population aged 18 years and older. The final sample consisted of 2,018 individuals. Of this sample, 52.6% were women. The mean age was 44.7 years (*SD* = 17.6, *Mdn* = 42.50). The average level of education was completion of at least some college (*M* = 6.2, *SD* = 0.87, *Mdn* = 6.0, range = 1–7)

Measures

Our dependent variable measured how much Internet users understand about how algorithms curate what they see in their search results. At present, there is no widely accepted operationalization of algorithmic knowledge. Therefore, we worked with the survey items that best matched our conceptual definition. Although the survey was not originally designed to focus on knowledge about algorithms, it included questions to this effect. We measured algorithmic knowledge with a scale created from component scores from a principal components analysis, using Kaiser normalization, of six items capturing different factors known to impact algorithmic curation (see Appendix Table A1). One component containing all six items was extracted, which explained 58.3% of the shared variance. Participants were asked, "Generally speaking, how much INFLUENCE do you think the following factors have on the results a search engine displays to you? In your opinion are the results based on . . .?" The items were "the popularity of different sites," "your location," "your past search history," "whether a website has optimized its online visibility," "relevance to your search terms," and "advertising or sponsorship fees paid to the search engine." Possible responses ranged from 1 (*no influence*) to 4 (*strong influence*). The higher an individual's score, the greater the algorithmic knowledge.

According to previous research on experience technologies, we assumed that both frequency as well as breadth of using search engines would affect how much individuals know about how algorithms work. Frequency of searching online for information was measured by asking participants, "How often do you use a search engine to find information online?" Possible responses ranged from 0 (*never*) to 5 (*more than once a day*; *M* = 4.3, *SD* = 1.1, *Mdn* = 5.0). Breadth of use of online search was measured with a scale calculated from the mean of responses to eight questions, which referred to a variety of purposes for which search engines might be employed. Participants were asked, "How often do you use SEARCH ENGINES for the following purposes?" Items included "Going QUICKLY to a specific website," "Looking for NEWS updates on a particular topic, event, or person," and "Finding ENTERTAINING content, such as music, videos, or jokes." Possible responses ranged from 1 (*never*) to 5 (*very often*; *M* = 3.6, *SD* = 0.79, *Mdn* = 3.6; see Appendix Table A2 for the full list of measures).

Building on previous research on knowledge gaps and digital inequalities, we included a number of socioeconomic variables. Education consisted of seven categories, ranging from 1 (*less than primary education*) to 7 (*college degree*; *M* = 6.2, *SD* = 0.87, *Mdn* = 6.0). Income was measured across nine categories, ranging from 1 (*less than $10,000*) to 9 (*more than $100,000*; *M* = 5.6, *SD* = 2.5, *Mdn* = 6.0).[2] It should be noted that 7.5% of the U.S. sample (*n* = 151) did not answer this question. Although this is a comparatively low number of missing cases for income data, it affects the overall number of missing cases. To measure race and ethnicity, respondents first indicated to which racial group they considered themselves to belong (White, Black/African American, American Indian/Alaskan Native, Asian, Native Hawaiian/other Pacific Islander, and mixed race/other). Respondents were also asked to indicate whether they were Hispanic, Latino/a, or Spanish. To include both race and ethnicity categories in analyses, we combined categories. Three racial groups consisted of very few respondents: American Indian/Alaskan Native (*n* = 17), Native Hawaiian/other Pacific Islander (*n* = 1), and mixed race/other (*n* = 67). Due to the small numbers, these three categories were combined. Final categories used in analyses were Hispanic (7.8%), non-Hispanic African American (5.9%), non-Hispanic Asian American (7.5%), non-Hispanic White (76.4%), and non-Hispanic other (2.4%). Throughout our analyses, we used deviation coding for race and ethnicity variables, which compared the mean of the dependent variable for a given group to the grand mean of all other groups. Other demographic variables included age (*M* = 44.7, *SD* = 17.6, *Mdn* = 42.5) and gender (52.6% women).

Previous work has evidenced the relationship between self-perceived skill and use of ICTs (Hargittai & Walejko, 2008). Accordingly, we included self-perceived search ability as a control. To measure self-perceived search ability, we asked, "Generally speaking, how would you rate your ABILITY to use a search engine like Google or Bing?" Possible responses ranged from 1 (*bad*) to 5 (*excellent*; *M* = 4.5, *SD* = 0.65, *Mdn* = 5.0).

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[2] As education and income are often related, we conducted collinearity testing. The items were not collinear and, therefore, both education and income were included in the analyses.

Results

To explore possible structural disparities in algorithmic knowledge (H1), we conducted a multiple regression analysis, controlling for socioeconomic features and search ability. As indicated in Table 1, Hypothesis 1 was supported. Education—as an indicator of socioeconomic background—was positively associated with algorithmic knowledge (β = .11, *SE* = .03, $p < .001$). The results also indicated that age was a negative predictor of algorithmic knowledge (β = −.12, *SE* = .002, $p < .001$). Gender and race/ethnicity were not significant predictors of algorithmic knowledge. The overall adjusted R^2 was relatively low for this model. Socioeconomic factors alone explained only 9.2% of the variance of algorithmic knowledge, suggesting other factors at play for which this first model did not account.

Table 1. Results of Multiple Regression Analysis Predicting Algorithmic Knowledge From Socioeconomic Background.

Variable	β	*SE*
Age (years)	−.124***	.002
Income ($)	.032	.010
Gender (female = 1)	−.006	.048
Education	.109***	.031
Race		
Hispanic	.073	.078
African American, non-Hispanic	.041	.086
Asian American, non-Hispanic	−.033	.081
Other, non-Hispanic	−.072	.135
Search ability	.220***	.040
Total R^2 (%)	.098***	
Adjusted R^2 (%)	.092***	

*$p < .05$. **$p < .01$. ***$p < .001$.

Next, we explored the structural roots of experience-based algorithmic knowledge building. In this, we proposed a positive relationship between socioeconomic background and frequency (H2) and breadth (H3) of use of online search. As expected, the results of a regression analysis showed that education, income, and age were significant predictors of frequency of use (see Table 2). Education (β = .09, *SE* = .03, $p < .001$) and income (β = .06, *SE* = .01, $p = .015$) were positively related to frequency of use, whereas age was negatively related (β = −.20, *SE* = .001, $p < .001$). Gender and race/ethnicity were not significant predictors of frequency of use. Similarly, education (β = .05, *SE* = .02, $p = .029$) and income (β = .05, *SE* = .01, $p = .031$) were significant positive predictors of breadth of use, whereas age (β = −.21, *SE* = .001, $p < .001$) had a negative relationship with breadth of use. Compared with all other racial/ethnic groups combined, being of Hispanic origin was positively related to breadth of use (β = .16, *SE* = .05, $p < .001$). Gender was not a significant predictor.

Table 2. Results of Multiple Regression Analysis Predicting Frequency and Breadth of Use of Online Search.

Variable	Frequency of online search		Breadth of use of online search	
	β	*SE*	β	*SE*
Age (years)	−.199***	.001	−.213***	.001
Income ($)	.057*	.009	.050*	.007
Gender (female = 1)	.013	.041	.029	.032
Education	.091***	.026	.050*	.021
Race				
Hispanic	.084	.069	.157***	.054
African American, non-Hispanic	−.015	.075	−.015	.060
Asian American, non-Hispanic	.029	.071	−.030	.056
Other, non-Hispanic	−.080	.114	−.052	.091
Search ability	.305***	.033	.308***	.026
Total R^2 (%)	.190***		.206***	
Adjusted R^2 (%)	.190***		.202***	

*p < .05. **p < .01. ***p < .001.

We then tested the relationship between experience with online search—as measured via frequency and breadth of use of search engines—and algorithmic knowledge. Hypothesis 4 suggested that frequency of use would be positively associated with algorithmic knowledge. Controlling for socioeconomic features and search ability, the results supported Hypothesis 4. Frequency of use was a significant predictor of algorithmic knowledge (β = .22, *SE* = .03, p < .001; see Table 3). Hypothesis 5 proposed that breadth of use would be positively related to algorithmic knowledge, even when controlling for frequency of use. This hypothesis was also supported (see Table 3). When including both breadth and frequency of use, breadth of use was a significant and strong predictor of algorithmic knowledge (β = .46, *SE* = .04, p < .001), but frequency of use was not. Education remained a significant predictor of algorithmic knowledge in both models. Notably, the standardized coefficient for breadth of use was nearly 5 times larger than that of education. Adding breadth of use to the model also increased the adjusted R^2 from 13.0% to 27.4%, showing that the variable accounted for a relatively substantial amount of the variance in algorithmic knowledge.

Table 3. Results of Multiple Regression Analysis Predicting Algorithmic Knowledge From Experience Variables.

	Model 1		Model 2	
Variable	β	*SE*	β	*SE*
Age (years)	−.084**	.002	−.040	.001
Income ($)	.016	.010	.004	.009
Gender (female = 1)	−.004	.047	−.013	.043
Education	.090**	.030	.093***	.028
Race				
Hispanic	.060	.076	−.001	.069
African American, non-Hispanic	.044	.084	.061	.076
Asian American, non-Hispanic	−.040	.080	−.040	.072
Other, non-Hispanic	−.059	.133	−.039	.120
Search ability	.151***	.042	.056*	.039
Frequency of search	.217***	.029	.032	.029
Breadth of search			.464***	.035
ΔR^2 (%)	.135***		.146***	
Total R^2 (%)	.135***		.279***	
Adjusted R^2 (%)	.130***		.274***	

*$p < .05$. **$p < .01$. ***$p < .001$.

Discussion

In the last 10 years, algorithms have become more deeply entrenched in our online information infrastructure, acting as gatekeepers and arbiters of truth (Gillespie, 2014). Unlike human editors, algorithms' work remains obscured and is not common knowledge (Eslami et al., 2015; Rader et al., 2018; Rader & Gray, 2015). The opacity of algorithms poses a problem for information acquisition on online platforms because individuals who are unaware of algorithms will not have an accurate or complete picture of the conditions by which information reached them. Moreover, inequities in the distribution of algorithmic knowledge will leave some better equipped to make good use of algorithmic systems as they seek to make sense of the world and their place in it.

The present study sought to explore whether algorithmic knowledge is unevenly distributed according to socioeconomic advantage. We also proposed and tested a process of knowledge building through experience. Consistent with a broader history of information and knowledge inequities, the findings suggest that an algorithmic knowledge gap exists within the context of online search, with higher SES populations exhibiting greater knowledge about how algorithms work than lower SES populations. As digital inequality and knowledge gap research suggest, this gap likely stems from the stratification of various resources, which affords more privileged groups greater advantages in the acquisition and processing of relevant information. Our results also suggest that experiences with online search provide opportunities for users to learn about the algorithms at work in this realm. Whereas merely using online search frequently does not necessarily lend insight, using online search for a variety of purposes allows users to occupy various vantage points and, thus, permits a more complete view of what is happening "under the hood." These findings correspond to previous research on experience technologies, or technologies that are difficult to understand without the insight afforded by engaging with a technology in a range of ways (Blank & Dutton, 2012; Dutton & Shepherd, 2006).

Degree of experiences with online search—measured in the present study via frequency and breadth of using online search—corresponds to socioeconomic inequality. This provides further evidence that algorithmic knowledge may be growing at a faster rate among those with greater socioeconomic advantages. Still, the findings invite cautious optimism as individuals' direct interactions with algorithmic platforms seem to afford knowledge accumulation to a greater degree than education, the only significant socioeconomic predictor in our final model. This is evidenced by the fact that the standardized coefficient for breadth of use was nearly 5 times larger than that of education. In light of this finding, it is possible that some knowledge may be acquired independently of the infusion of information into the social system, that is, as a function of socialization processes, mass media coverage, and formal education. Yet, we acknowledge that additional variables not tested in this study may contribute to knowledge gaps. For example, those who use search engines for a broader range of purposes may be more tapped into media coverage of algorithms that provides greater opportunities for learning about them. Future work should take this into consideration.

Algorithmic knowledge affords individuals the ability to question and critique representations of their world, as reflected to them via algorithmic output like search results. Without some awareness of algorithmic curation, users may treat the information they receive from online platforms as unadulterated truths. In this case, the knowledge they construct from these platforms will likely reflect the biases inscribed in the design of algorithms mediating information in these spaces (Friedman & Nissenbaum, 1996; Nissenbaum & Introna, 2000; Noble, 2018). The knowledge gaps documented in this study suggest that some individuals are more likely to approach information online with a different set of expectations than others. Beyond questions of critical consumption of information, recent studies have shown that knowledge of platform algorithms can contribute to gains in both monetary and social capital (Cotter, 2019; Klawitter & Hargittai, 2018). Indeed, digital divide and inequality research has long theorized the mutually shaping relationship between digital participation and offline resources (e.g., van Deursen & Helsper, 2015; J. A. G. M. van Dijk, 2005). The delegation of crucial decision making to algorithms in economic, cultural, social, and personal fields of society could grant advantage in these realms to those with greater knowledge of algorithms' operations and underlying logics. This is an especially important point as algorithmic processes, in contrast to processes centered around human discretion, may be more easily learned and gamed (Zarsky, 2016). Our findings suggest that more privileged groups are better positioned to benefit from algorithmic knowledge than those with fewer resources.

Still, our findings pertain to knowledge of algorithms used by search engines and we do not yet know whether they extend to other types of algorithmic systems. We chose this domain because of its important role in knowledge building and production more generally. However, knowledge of algorithms within other types of platforms—particularly those that use algorithms for tasks beyond ranking for personalization—will need to be explored further to assess whether the present study's findings hold for other contexts. Algorithmic ranking in online search does share some commonalities with the algorithmic ranking on social media. Still, social media and online search differ in notable ways, including how individuals engage with these platforms. As such, future studies need to clarify whether and how knowledge about algorithms in domains beyond online search relates to socioeconomic background and experience.

As one of the first quantitative studies assessing algorithmic knowledge, the present study relied on a fairly simple operationalization of algorithmic knowledge informed by the known, basic factors that influence algorithmic curation in online search (Patel, 2015). In some ways, this operationalization might be considered a conservative estimate of the greater depths of individuals' knowledge. Digital skills are composed of a range of sequential skills that build on one another (van Deursen & van Dijk, 2010). Algorithmic knowledge may also be sequential in that the kind of basic knowledge referred to in the present study lays the foundation for more advanced insight. Yet, from our operationalization, we cannot definitively say whether the determinants of algorithmic knowledge we evidenced—namely, education and experience with online search—would relate to more complex knowledge. Previous work has indicated that knowledge gaps according to socioeconomic background are harder to see for rudimentary knowledge (Viswanath & Finnegan, 1996). This suggests that socioeconomic background likely would also correspond to more in-depth algorithmic knowledge. By contrast, the complex and dynamic nature of algorithms deployed on online platforms, particularly those that rely on machine learning, may lead to a ceiling effect for algorithmic knowledge derived from experience. Experience may only afford basic insight about algorithms, as investigated in the present study. Thus, the opacity of algorithms may preclude users from accumulating sufficient algorithmic knowledge for critical assessments of information flows online through use alone. Although our findings suggest that experience can aid in basic knowledge building, education may persist as the primary predictor of more complex algorithmic knowledge.

Finally, algorithmic knowledge does not supplant critical thinking skills or information literacy. Possessing some knowledge of algorithms does not entail its effective mobilization in assessing and making sense of information in context. Algorithmic knowledge can be fairly abstract, which means that individuals need to be well equipped to make connections between the features of information delivered on algorithmic platforms and their knowledge of how algorithms mediate information. Just as digital literacy entails skills linked to technical aspects of digital tools, as well as those related to assessing content (van Deursen & van Dijk, 2010), a broader algorithmic literacy may, too, entail familiarity with how algorithms work as well as the ability to assess their information outputs. In this case, once again, education may be the best means of fostering good information practices vis-à-vis algorithms. Future work should further investigate the drivers of different dimensions of more in-depth algorithmic knowledge, as well as how information literacy and algorithmic knowledge may interact in online information encounters.

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Appendix

Table A1. Algorithmic Knowledge: Descriptive Statistics, Principal Components Loadings.

Generally speaking, how much INFLUENCE do you think the following factors have on the results a search engine displays to you?	*M*	*SD*	Component loading
Website has optimized its online visibility	2.84	0.91	.809
Your geographic location	2.74	0.90	.760
Your past search history	2.88	0.88	.771
The popularity of different sites	2.91	0.92	.823
Relevance to your search terms	3.15	0.81	.680
Advertising or sponsorship fees paid to the search engine	2.67	1.05	.731

Table A2. Breadth of Use of Search Engines: Descriptive Statistics.

How often do you use SEARCH ENGINES for the following purposes?	*M*	*SD*
Going QUICKLY to a specific website	3.82	1.00
Finding INFORMATION on a specific topic	3.98	0.90
Looking for NEWS updates on a particular topic, event, or person	3.55	1.04
Finding information about POLITICS or current events	3.26	1.13
Finding information about a MEDICAL or health question	3.34	1.07
Looking up facts, answering a FACTUAL question	3.80	0.95
Checking the ACCURACY of news or information you've found	3.44	1.07
Finding ENTERTAINING content, such as music, videos, or jokes	3.29	1.21