Encountering Algorithms: An investigation of algorithmic literacy among a sample of undergraduate students

by

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Abstract

Algorithms are ubiquitous, playing important roles in nearly every sector of contemporary society. This thesis investigates levels of awareness, and knowledge about, algorithms among a sample of undergraduate students. The project was divided into two phases, the first of which entailed conducting a systematic review of algorithmic literacy research published over the last 25 years in the fields of media and literary studies to ascertain how this concept is defined and the competencies with which it is associated. The review findings informed the second phase of the project which entailed conducting four focus group discussions with a sample of 25 undergraduate students. The findings suggest current frameworks and approaches to studying algorithmic literacies do not lend themselves to capturing the multiple dimensions and competencies undergirding this concept. This, in turn, suggests that there is much to be gained for focusing research and policy efforts on algorithmic litérac*ies* as opposed to algorithmic literacy

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Chapter 1 - Introduction

Algorithms are a fundamental component of the contemporary technological landscape (Cotter & Reisdorf, 2020). Originating from the field of mathematics, the term algorithm was initially used in reference to the step-by-step methods required to perform numerical arithmetic calculations (Miyazaki, 2012). Evolving during the mid-twentieth century in tandem with the development of scientific computation and programming languages, the word algorithm came to designate specific computer-programmed procedures that follow defined sets of instructions to process data and produce desired outputs (Miyazaki, 2012; Danaher, 2016; Kitchin, 2017). Put simply, an algorithm is a predetermined assemblage of clear, computer-implementable instructions that can be used to perform a wide-ranging set of complex computational tasks or to solve problems otherwise impossible to resolve by hand or other techniques. Today, the systems and software used, developed, and implemented across public and private sectors are powered by, and reliant on, algorithms and other artificial intelligence (AI) technologies (Danaher, 2016; Kitchin, 2017). Indeed, algorithmic systems now serve as vectors, mediators, producers, and regulators of a wide range of everyday activities (Andrejevic, 2019; Bucher, 2018; Burgess, Albury, McCosker & Rowen, 2022; Eubanks, 2018; O'Neil, 2017; and Zerilli, 2021).

With computer sciences and mathematics "coming together in powerful ways to influence, shape and guide our behaviour and the governance of our societies" (Danaher et al., 2017, p.1), algorithms and AI have soared to the forefront of conversations about science, technology, innovation, and social policy (Danaher, 2016; Hargittai & Micheli, 2019; Tsamados et al., 2020; Mittelstadt et al., 2016, O'Neil, 2017; Eubanks, 2018). The term artificial intelligence (AI) refers to "any human-like intelligence exhibited by a computer, robot, or other machine." (IBM, 2020). AI enables computers and machines to perform tasks similar to those performed by the human mind such as learning from models and practices, distinguishing objects, understanding and using linguistics, making decisions and solving problems. AI can be, and is, used to perform functions such as driving a car (IBM, 2020), and scavenging the surface of planets (Achenbach et al., 2021). This said, it merits keeping in mind that it is algorithms that facilitate and provide the instructions for almost every AI device created. However, not every type of algorithm is an AI or a machine learning system. Some algorithms follow pre-defined instructions and perform explicit tasks that makes their processes automated, but not artificially intelligent per se (e.g. Bubble sort is a kind of algorithm that is not artificially intelligent (Kolade, 2022). This type of algorithm is used to sort and arrange sets of values in ascending or descending order. It is notably used to sort contact lists in alphabetical order on smart phones and tablets (Kolade, 2022).) This being said, machine-learning algorithms[1] programmed to consistently learn how to perform new tasks and produce new models from datasets are, in fact, artificially intelligent technologies (Gonfalonieri, 2019).

Today, algorithmic systems are found at the center of almost every modern practice. Among other things, they curate social media newsfeeds (Elsami et al., 2015), organize search engine query results (Bakke, 2020), trade stocks on Wall Street (McDowell, 2021), and produce small online news reports (Diakopoulos, 2017). Moreover, their application extends far beyond the digital realm, with algorithms increasingly being incorporated into an ever-growing range of decision-making activities to support, or supersede, human judgment and expertise. For example, scientists at the Centro Nacional de Investigaciones Cardiovasculares (CNIC) in Madrid Spain designed an algorithm that weighs a variety of variables to generate personalized prognostics of individual cardiovascular health (Foreman, 2020). In early 2020, the International Baccalaureate

[1] A machine-learning (ML) algorithm refers to a particular semi-autonomous or autonomous type of algorithm programmed to detect and use patterns of knowledge existing within massive amounts of data to create new prediction models (Diakopoulos, 2019; Mittelstadt et al., 2016; Lepri et al., 2018).

Spanish exam used an algorithm to assign grades to over 160 000 students in lieu of the usual in-person exams that could not take place due to the Covid-19 pandemic. The prestigious global program used an algorithm to ‘predict’ IB students’ grades based on personal information and past performance (Broussard, 2020). In California, a ‘crime prediction algorithm’ is being considered to replace cash bails and to dictate whether, in accord with an algorithmically generated ‘risk score,’ individuals should be jailed while awaiting trial (Scher, 2020). Likewise, the Vancouver Police Department in British-Columbia uses an algorithmic policing system to predict and identify potential criminals and delinquency hotspots based on data gathered from previously documented infractions (McQuigge, 2020).

1.2 Literacy or Multiliteracies?

Throughout the last quarter century, the extension of the traditional concept of literacy beyond “the ability to read and write” (Cambridge English Dictionary, 2020) has coincided with the growth of inter-networking and other digital technologies. In the early 2000s, digital literacy had come to be seen as essential to the development of a well-informed, critical and negotiated understanding of the numerous cultural and economic dimensions of technology (Aufderheide, 1992; Duncan, 2006; European Commission, 2007). In Canada for example, federal policies for the digital economy consider that digitally literate individuals are vital to the prosperity of the information economy and to the empowerment of an engaged and united population (Shade & Shepherd, 2013). In recent years, algorithms have become increasing pervasive in almost every aspect of human activity (Hasselberger, 2019). Echoing debates from the early days of the new millennium, the growing reliance on the use of mathematical models to organize, perform and guide decision-making processes within various sectors and institutions has sparked countless discussions about the need for citizens to acquire at least basic knowledge of algorithms, and their ethical implications, if they are to be well-informed, functioning members of contemporary society (O'Neil, 2017; Noble, 2017; Bucher, 2018.)

The pervasiveness of information and communication technologies (ICTs) in just about every facet of contemporary daily life has transformed literacy practices. Reflecting these changes, the concept of literacy has come to be understood as encompassing the capacity to integrate the skills necessary to effectively participate in society by making effective use of information (Campbell, 1990) including, "the ability to identify, understand, interpret, create, communicate and compute, using printed and written materials associated with varying contexts" (UNESCO, 2004. P.13). This definitional shift is a product of more and more attention being given to how individuals understand, interpret, critically analyze, and compose texts[2] of various kinds along with a growing recognition that literacy practices stem from social practices and technologies (Street, 2012; Collins, 1995; Dabrowska, 2019; Bawden, 2001; Hobbs, 2006). This, in turn, has contributed to a movement away from conceptualizing literacy as a uniform phenomenon toward the notion of multiliteracies.

The emergence of the notion of multiliteracies coincided with the mainstreaming of the internet and the popularization of the World Wide Web in the mid-to-late 1990s (West, 2019). This concept was introduced by a group of scholars known as the New London Group[3] who focused on the intersection of literacy theory and technological innovation, and who agitated for a pluralistic conception of literacy reflecting the challenges and realities fostered by emergent

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[2] Street (2012, p.24) emphasizes that the definition of 'text' is not limited to alphanumeric characters and script. In their view, it also encompasses "the kinds of icon and the signs evident in computer displays like the Microsoft® Word package, with all its signs, symbols, boundaries, pictures, words, texts, images and so on."

[3] The New London Group is a collective of ten scholars who first met in 1994 to discuss the evolving world of communications. Their shared concern for language and education motivated them to collaboratively write an agenda for what they called a "pedagogy of multiliteracies." See, https://newlearningonline.com/kalantzis-and-cope/research-writing

technologies (Cope & Kalantizis, 2004, 2009). According to the New London Group, literacy is best understood as a multimodal phenomenon: a dynamic, multifarious competence that progressively evolves to integrate daily media and cultural practices (New London Group, 1996; Kalantiz & Cope, 2004, 2009).

The fundamental tenet of the multiliteracies perspective asserts that new literacies emerge from new communication practices that, in turn, are manifested through new social practices (Cope & Kalantzis, 2009). This idea is illustrated by the identification of the need for various 'skill-based literacies' such as digital literacy and media literacy in the so-called knowledge economy or digital age (Shade & Shepherd, 2013; Cope & Kalantzis, 2009). Writing in the late 1990s, Gilster (1997) and Gilster & Pool (1997) posited that literacy in the digital age ostensibly was a modern manifestation of print literacy. Engaging with multiple components of digitality, Gilster drafted a blueprint for digital literacy that was anchored in a list of essential aptitudes to attain digital literacy for the World Wide Web. Central to Gilster's blueprint was an acknowledgment that content evaluation and critical thinking about online information was the most important competence to master. To wit, he asserted that it is impossible for anyone to understand information gathered online without evaluating its sources and placing it into context (Gilster, 1997; Gilster & Pool, 1997) and went so far as to suggest deeming digital literacy as an "essential life skill— 'becoming as necessary as a driver's licence'—or even (presumably metaphorically) as a 'survival skill'" (Bawden, 2001, pp.22).

Since then, the concept of digital literacy has evolved to comprise an ever-growing number of complementary literacies pertaining to differing digital communication channels. This is evidenced by the contemporary propensity to speak of digital literacy in its plural form – digital literacies (Dudeney, Hockly, & Pegrum, 2018). Moreover, contemporary definitions of digital literacy tend to be anchored in the idea that this concept “typically refers to the technical, cognitive, and sociological skills needed in order to perform tasks and solve problems in digital environments” (Shade, 2013, p.2). However, one needs to approach such understandings with caution insofar as the terms ‘literacy’ and ‘skill’ are not synonymous. Whereas the latter is commonly used to describe more pragmatic, interactive uses of specific knowledge in practical settings, the former encompasses the general dimensions of competence and understanding (van Dijk & van Deursen, 2014). In other words, ‘skill’ is a component of ‘literacy’.

Digital literacies have become important building blocks for modern life. In the educational domain, for example, school curriculums are increasingly emphasizing the importance of digital competencies and new literacies to prepare students for social life, employment and citizenship (Selwyn & Facer, 2014; Dudeney, Hockly, & Pegrum, 2018). Indeed, it often is claimed that citizens wishing to participate in the contemporary economy need to master multiple digital literacies in their lifetime (Trilling & Fadel, 2009; Dudeney, Hockly, & Pegrum, 2013), and these literacies need to be continuously updated through the acquisition of new skills and understandings from a highly dynamic ever-changing information environment (Bawden, 2008; Koltay, 2011). One of these new literacies, and the focus of this thesis, is algorithmic literacy.

This thesis examines the intersection of algorithmic literacy with the ways in which young people encounter algorithms in their daily lives. The research for this project was divided into two phases. Phase 1 was aimed at identifying the parameters of the concept of algorithmic literacy. It involved conducting a systematic review of the literature of algorithmic literacy research published over the last 25 years in the fields of media and literary studies. The objective here was to assess whether there exists any consensus, or agreement, on a common definition of this concept. The research question guiding this first phase asked; *From a socio-technical perspective, what are the key components of algorithmic literacy?*

The findings that emerged from Phase 1 were then used to create protocols to guide focus group discussions with a sample of undergraduate students enrolled at the University of Ottawa. To this end, the Phase 2 focus group discussions sought to investigate what the participants knew about algorithms and how they perceive and negotiate their daily interactions with algorithmic systems. As such the research question guiding the second phase of my project asked: *What is the level of algorithmic literacy among undergraduate students at the University of Ottawa?*

The discussion in the next section sets out how the presentation of my investigation of this concept is structured.

1.3 Thesis Structure

The thesis is divided into five chapters. This first introductory chapter has provided a brief overview of the background and context for the discussion presented in the subsequent chapters. Chapter 2 offers an overview of the concept of algorithmic literacy along with an examination of some of the key policy issues and challenges arising from the ubiquity of algorithms in contemporary society. This discussion provides the foundation for the systematic review of the literature presented in Chapter 3. The findings emerging from this review of algorithmic literacy research published over the last 25 years in the fields of media and literary studies shows that there is no set definition regarding what algorithmic literacy is or entails. Nonetheless, the major finding of this theoretical investigation revealed 5 overarching themes that recur across all algorithmic literacy definitions included in the literature review. This insight served as the basis for the focus group discussions described in Chapter 4. The discussion in this chapter details the research methodology informing the design and content of the focus group discussions and presents the findings that emerged from these meetings. The discussion in Chapter 5 wraps up the thesis. It sets out the key findings and contribution to knowledges emerging from this project, along with a discussion of the principal limitations of this work, and potential directions for future research.

Chapter 2 – Toward an understanding of algorithmic literacy

The discussion in this chapter provides an overview of algorithms and the associated concept of algorithmic literacy. The discussion is divided into four sections. The first examines the notion of algorithmic bias. Here, I look at some of the noteworthy issues and challenges associated with the development and implementation of algorithms in various contexts. Section two focuses on the concept of algorithmic awareness by examining contemporary thinking about what algorithmic awareness entails and how it is acquired. In section three, I turn my attention to the concept of algorithmic literacy and some of the challenges associated with studying and defining this concept. Section four concludes the discussion.

2.1 Algorithmic Bias

The growing pervasiveness of algorithms in decision-making activities raises ethical concerns about the consequences of the decision outcomes they generate (Bucher, 2018; O'Neil, 2016; Noble, 2018; Eubanks, 2018; Diakopoulos, 2019; Finn, 2017; Hasselberger, 2019; Oldridge, 2017; Mueller & Dhar, 2020; Kids Code Jeunesse (KCJ) & the Canadian Commission for UNESCO (CCUNESCO), 2020). These concerns largely revolve around such issues as privacy, inequality, discrimination, democracy, (data-)surveillance and human rights (O'Neil, 2016; Hasselberger, 2019, pp.978; Sederstrom, 2020; Eubanks, 2018; Herring, 2020; Zuboff, 2019; Henley & Booth, 2020). What is more, the implementation of algorithmically enabled platforms to guide social programs and services such as unemployment benefits, child support, as well as housing and food subsidies has given rise to already vulnerable populations being further marginalized (Eubanks, 2018; Pilkington, 2019; Alston & Van Veen, 2019; Alston, 2020; McCully, 2020). A common concern in this regard is the potential for, and extent to which, preoccupations with efficiency, budget-savings, and fraud-detection motivate the development and adoption of artificially intelligent (AI) technologies that perpetuate poverty, discrimination, and racism (O'Neil, 2016; Noble, 2018; Eubanks, 2018; Finn, 2017). Focusing on events in the United States, Eubanks (2018) documents how the automating of a welfare eligibility system in the state Indiana resulted in innumerable technical oversights that further disenfranchised those most in need of public services. She found that between 2006 and 2008, a period after which the state government had implemented an algorithmically mediated decision-making process to assess welfare eligibility, the rate of applicants erroneously denied social supports for which they qualified increased from 1.5% to 12.2%. More recently, Dobson (2022) has identified a number of shortcomings with the algorithmic governance of the province of Ontario's social assistance program including the elimination of any discretion that previously was available to case workers in finding appropriate solutions for specific cases.

While some consider algorithms to be a viable solution to the ethical scarcity of human judgement (Mullainathan, 2019), others express concerns about the elimination of interpretative flexibility in decision-making situations that directly affect human lives. Advocates of algorithmic systems, for example, tend to zero-in on issues of efficiency, impartiality, and optimization as key benefits (Diakopoulos, 2019, Andrejevic, 2019). Some reported achievements in this regard include changes in journalism practice where—among other things—the optimization of the data management process facilitates and accelerates investigative journalism queries (Diakopoulos, 2019); in child protection services where predictive algorithms pinpoint areas where increased human resources and support need to be deployed (Sederstrom, 2020); in grade school education where automation is used to create a personalized learning experience for each child (Morrissey, 2020); and in medicine—notably to detect breast cancer earlier among higher risk patients (Izmirlieva, 2020).

By contrast, critics contend that how algorithms accomplish the tasks they are designed to carry out (i.e., algorithmic operational criteria) are expressions of human values and, therefore, render algorithms anything but neutral (Naughton, 2016). In line with this view, Barocas and Selbst (2016, p. 674) assert that even without being specifically programmed to do so, algorithms "can reproduce existing patterns of discrimination, inherit the prejudice of prior decision makers, or simply reflect the widespread biases that persist in society" precisely because they 'learn' on the basis of existing data that may well reflect various biases. Discrediting the use of algorithmic processes for their apparent lack of impartiality has initiated conversations about whether neutral decision-making processes even exist considering that decisions rendered by humans are also inevitably skewed by personal inherent biases (Naughton, 2019; Mullainathan, 2019; Barocas & Selbst, 2016; O'Neil, 2017; Eubanks, 2018).

This said, both camps acknowledge that neither process is completely impartial (Lepri et al., 2018; Mullainathan, 2019; Barocas & Selbst, 2016). Algorithms are not entirely neutral entities because bias is inevitably embedded in their code which can, in turn, reproduce and/or magnify pre-existing inclinations (Woodruff et al., 2018; Lepri et al., 2018; Tsamados et al., 2020). Likewise, the data in the data sets used to train algorithms may skewed in any number of ways thereby propagating a host of less than socially desirable outcomes (Dobson 2022; Eubanks 2018; O'Neill 2017; Noble 2017). To this end, numerous reports have found that algorithmic bias can either be the product of human error, or the result of skewed data being fed into a machine-learning (ML) algorithm (Baer, 2020; Danaher et al., 2017; Barocas and Selbst 2016; Lepri et al., 2018; Mittelstadt et al., 2016).

When implemented, machine-learning algorithms can autonomously define or modify their decision criteria depending on the information from which they have previously learned

(Mittelstadt et al., 2016; Bucher 2018). Put simply, if the information on which a machine-learning algorithm feeds is biased, or flawed in some other way, the algorithm's decisions will inevitably reproduce these limitations. For example, in some instances, machine-learning algorithms used for profiling and policing purposes have been shown to discriminate against marginalized communities by making decisions based on factors such as ethnicity and income level that reinforce racism and classism (Barocas and Selbst 2016; Eubanks, 2018; O'Neil 2017). In such instances, it often is the data as opposed to the algorithm that is biased insofar as it is the data rather than the code itself that reflects deeply rooted underlying issues in society (Mittelstadt et al., 2016; Eubanks, 2018). Bucher (2018), Barocas and Selbst (2016), Eubanks (2018), O'Neil (2017), and Mittelstadt et al., (2016), among others all emphasize the importance of those who develop the technology, those who use it, and those who find themselves at the receiving end of its outputs to acquire knowledge about such issues. This, they, and others, claim is an important first step towards mitigating the negative social consequences to which the pervasiveness of algorithmic decision-making can, and often do, give rise.

It is also important to note that errors and situations of unfairness occur even when data integrity has not been compromised. This is because algorithms can, and often do, entrench biases on their own. Gupta (2020), Lepri et al. (2018), Barocas and Selbst (2016), and Knight (2017) have all investigated coder-perspectives on the ethics of algorithms. Noting that big tech companies and major organizations often fail to offer adequate ethical and/or moral training sessions for their engineers, they suggest that the propensity of current control frameworks – which are rooted in the micro-division of work and the hyper-specialization of engineers – often precludes engineers from grasping important contextual awareness about the technologies they are developing. Further complicating matters, crucial stakeholders who use and develop algorithmic systems are also seemingly reluctant to take action to fix identified shortcomings with the systems they design (Knight, 2017; O'Neil, 2016; Woodruff et al., 2018). It seems plausible that this may be due, at least in part, to Gupta's (2020) and Knight's (2017) observation that, when engineers notice bias or unfairness in the architecture of the technology, reporting their observations may potentially threaten their livelihood.

This said, governments, NGO's, subject matter experts and other independent organizations from around the world are all grappling with the ethical consequences of AI technologies, and innovation in this domain more broadly. Several countries have begun to implement National AI strategies, regulations, and policies to frame the development of artificial intelligence (including machine-learning algorithmic applications) and to protect the interests of their publics (Gesley, 2019). For example, in 2017, the Canadian government funded the development of a Pan-Canadian Artificial Intelligence Strategy, the first of its kind, to advance national AI initiatives and foster a collaborative and ethical AI ecosystem (CIFAR, 2021). In the same year, the 2017 *Montréal Declaration for a Responsible Development of Artificial Intelligence* (Montréal Declaration) set out guiding principles for the ethical development of AI technologies and applications with respect to human values and technological sustainability. Similarly, in July 2020, the United Nations Educational, Scientific and Cultural Organization (UNESCO) launched a worldwide public consultation on the ethics of artificial intelligence.

Commenting on these types of initiatives, Latzer and Festic (2019) express reticence about the potential risks associated with developing policies that supposedly tackle algorithmic concerns in the absence of more data about the end-user experiences and perspective. Some of the most notable gaps in the evidence pertain to such issues as: algorithmic perception (Woodruff et al., 2018; Ytre-Arne & Moe, 2020); assessing algorithmic knowledge and/or skill (Hargittai &

Micheli, 2019; Latzer & Festic, 2019); and contextually appropriate research methods (Latzer & Festic, 2019; Hargittai & Micheli, 2019).

2.2 Fostering algorithmic awareness

Woodruff et al., (2018) contend that many of the challenges noted in the previous section are, in no small measure, a consequence of low levels of algorithmic awareness among the general population. Building on this concern, Cotter & Reisdorf (2020; see also DeVito et al., 2018; DeVito, Gergle, & Birnholtz, 2017) define two levels of cognition for search engine algorithm awareness: basic and advanced. Although both relate to functionality, the former focuses on awareness of the algorithm's intervention in the display of search results, whereas the latter centres on "insight about the principles and methods of software development that underlie algorithms" (Cotter & Reisdorf 2020, p.474). Hargittai et al. (2020, p.771) adopt a different though complementary view of algorithmic awareness, defining it in relation to "knowing that a dynamic system is in place that can personalize and customize the information that a user sees or hears." Rainie and Anderson (2017) echo this idea, suggesting that internet users must acquire and develop deeper understandings about the ways in which algorithms affect online experiences through processes of personalisation and prioritization.

For their part, Elsami et al., (2015) define algorithmic awareness as merely being cognisant of an algorithm's existence. They advanced this definition in their investigation of levels of awareness about the Facebook news feed algorithm, in which they found that 62.5% (n=25) of their sampled population (N=40 adults and students of all age ranges) were not aware of this algorithm's existence. Similar conclusions have also been advanced by Powers (2017), who found low levels of awareness among American college students of Facebook and Google's algorithmic news personalization practices.

Such findings raise questions about the state of algorithmic knowledge across societies. Young adults constitute a group who tend to be heavily subjected to algorithmically mediated interactions insofar as using apps and social media platforms is a characteristic feature of the daily lived experiences of many in this age demographic. Particularly noteworthy in this regard is Google's search engine. Statistics show that Google the most widely used search engine of all time, representing 91.94% of the global search market in December 2021 (Pitchkites, 2022). Furthermore, the frequency of use is documented as being correlated with age as 80% of Google users between the ages of 13 – 21 use the search engine more than three times per day (Pitchkites, 2022). However, there is a growing body of evidence signalling the ways in which marginalized communities are exponentially harmed by the outputs the Google search engine generates, especially in relation to matters of race and gender identity (Noble, 2018).

Similar concerns have been expressed about chatbots.[4] Designed to convey particular points of view and opinions, chatbots are often mistaken as productive social actors online due to their language processing abilities (Diakopoulos, 2019). There are countless reports of bots being used with malicious intent and/or in deceitful ways to propagate spam, instigate and perpetuate political clashes, convey the presence of false audiences/followers, influence political campaigns by fostering the spread of mis- and dis-information (see for example, Susskind, 2018; Confessor & al., 2018; and, Hsu & Thompson, 2023). Recently, even the chatbots created to assist individuals with various tasks and queries including support for mental health crises have been criticized for their potentially harmful responses and dangerous outputs they produce (see for example, Marche,

[4] Chatbots are AI algorithms that interact autonomously with users to stimulate online human interactions and to facilitate the diffusion and production of information found on social media and other platforms.

2021; and, Browne, 2022).[5] Bearing in mind the negatives uses with which chatbots often are associated, the global Covid-19 pandemic illustrated some of the potential virtues they afford insofar as they were employed by governments, private companies and healthcare organizations to mitigate and counter the spread of online misinformation about this public health crisis (Benavides, 2021; and Taylor, 2021). More specifically, chatbots were deployed within certain digital spaces (e.g., websites and social media platforms such as twitter) to answer questions, present factual information, and to alleviate any potential concerns regarding the Covid-19 vaccines and other related healthcare matters (see Benavides, 2021; Taylor, 2021). Correspondingly, a July 2021 report published by Research Dive[6] estimated that the global chatbot market will, by 2027, generate revenues of approximately $19,570,000 USD, implying a compound annual growth rate (CAGR) of 28% for the projected period (Research Dive, 2021; Yahoo Finance, 2021).

Activism around the issue of education and awareness about algorithms has been expanding, especially with regard to promoting critical thinking about both their use and how they function (see: Bucher, 2018; O'Neil, 2016; Noble, 2018; Eubanks, 2018; Diakopoulos, 2019; Finn, 2017; Hasselberger, 2019; and Oldridge, 2017). As Reisdorf and Blank (2021) put it, algorithmic literacy involves the capacity to know and understand the ways in which algorithms affect what users do and see online. To this end, nascent research and advocacy initiatives have sought to improve public knowledge about algorithmic systems and to increase awareness about their latent consequences. In Canada for example, the Canadian Commission for UNESCO (CCUNESCO)

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[5] Onur & al., (2017) suggested that some 9 to 15% of all twitter accounts – or 48 million profiles – were actually bots. Wojcik & al., (2018) estimated that in 2018 bots were accountable for two thirds of the tweeted links to popular news sources and websites.

[6] Research Dive is a market research firm which specializes in performing research and analyses of various markets across different verticals. They have published several reports about the impact of the Covid-19 pandemic worldwide. https://www.researchdive.com/covid-19-insights

collaborated with Kids Code Jeunesse (KCJ)[7] to launch *The Algorithm Literacy Project*[8] (Morello, 2020; Kids Code Jeunesse (KCJ) & the Canadian Commission for UNESCO (CCUNESCO), 2020). This English/French bilingual campaign was implemented to educate youth about algorithms and to improve their critical algorithmic thinking capacities.

Internationally, the *Seoul Declaration on Media and Information Literacy for Everyone and by Everyone* underlines the importance of reinforcing global media and information literacy competencies and urges technological stakeholders to assume a more accountable role in tackling issues relating to media and information literacy (UNESCO, 2020). Another noteworthy initiative, the *Algorithmic Justice League,*[9] is a U.S-based organization focused on revealing the consequences of artificial intelligence on society by increasing public awareness, providing empirical research to sustain their campaigns, supporting impacted communities, and inciting researchers, policymakers, and industry practitioners to mitigate AI bias and harms (Algorithmic Justice League, 2020).

The underlying premise of such advocacy work is that informed individuals are better equipped to understand and take position on the issues regarding the use and development of algorithmic systems and, hence, are likely to be better able to mitigate the potentially negative effects of these systems. The fundamental idea here asserts that the development of basic critical knowledge about algorithms fosters awareness and will enable individuals to take part in the conversations regarding the types of algorithmic processes that should and should not be

[7] Kids Code Jeunesse is a Canadian not for profit organization that is based in Montréal, dedicated to helping kids develop coding and computation thinking skills. See, https://kidscodejeunesse.org/

[8] The Algorithm Literacy Project is a Canadian educational initiative aimed at educating elementary school children and pre-teenagers about the algorithms they encounter online. Through interactive videos, digital booklets, and various activities, children are brought to learn more about algorithms and encouraged to develop critical thinking skills. See, https://algorithmliteracy.org/

[9] See, https://www.ajl.org/

implemented in different contexts and settings. As algorithmically powered platforms and automated data-mining systems progressively shape online experiences, the capacity to interrogate and negotiate with the experiences they produce is increasingly important (Dasgupta & Hill, 2020; Burgess, Albury, McCosker & Wilken, 2022; Bucher, 2018; Cheney-Loppold, 2017; Kitchin, 2021; & Zuboff, 2019).

2.3 <u>From algorithmic awareness to algorithmic literacy</u>

Given the complexity and relative novelty of algorithms, the issue of algorithmic literacy remains relatively under-examined. Details about the inner-workings of algorithms and algorithmic systems are obscure because the decision-making criteria on which they rely usually are concealed by layers of code and protected by trade-secret legislation (Pasquale, 2015; Perel & Elkin-Koren, 2017; Ananny & Crawford, 2018; Hargittai & Micheli, 2019; Bucher, 2018; Cotter & Reisdorf, 2020). The lack of transparency about algorithms means that much of the understanding about how they actually function remains limited to relatively few individuals (Perel & Elkin-Koren, 2017; Hargittai & Micheli, 2019; Cotter & Reisdorf, 2020; and Bucher, 2018).[10] This, in turn, impedes the development of appropriate metrics to evaluate of individual algorithmic skills, especially those relating to the technicality of these systems (Hargittai & Micheli, 2019). Yet, the consequences algorithms engender for society – both good and bad – are matters of public concern and have, as noted above, fomented growing advocacy for increased algorithm awareness.

In response, data scientists, social scientists, humanities' scholars, policymakers, and activists have begun collaborating to investigate the performative and normative aspects of data science practices and to address legal, ethical, and social issues arising from the pervasiveness of

[10] Hence, algorithms are commonly referred to as 'black boxes.' See, for example, Pasquale (2015), and Hargittai & Micheli (2019).

algorithms (Pfeffer & Mayer, 2019; Gillespie & Seaver, 2016; Moats & Seaver, 2019; and Finn, 2017). This work has, in turn, spawned the emergent field of critical algorithm studies. The latter broadly encompasses two types of research studies. The first places algorithms as the central unit of analysis and attempts to uncover the inner logics and mechanisms guiding their operation (see for example: O'Neil, 2016; Pasquale, 2015; Citron & Pasquale, 2014). The second focuses on the socio-technical context within which algorithmic applications are situated and focuses on the observable, concrete effects algorithms engender on social practices and society writ large (see for example: Bucher, 2018; Latzer & Festic, 2019; Mittelstadt et al., 2016; Eubanks, 2018; Crawford, 2021).

Adherents of the first approach suggest algorithmic literacy is contingent, in part, upon understanding the mathematics and coding that command algorithmic outputs. Particularly dominant in the domains of computer sciences, mathematics, and engineering, this technical-centered approach places agency in the code of the algorithm itself. As such, proponents of this view contend that the most important element to consider when studying algorithms is the engineered code that commands what algorithms do. Advocates of this viewpoint maintain that without knowing the mathematical equations behind the process, it is impossible to fix or even fully understand the issues perpetuated by algorithms and/or to hold accountable the people involved (O'Neil, 2016; Pasquale, 2015; and Citron & Pasquale 2014).

By contrast, the second approach, which is anchored in the humanities and social sciences, eschews the black box notion of algorithms. Its proponents contend that the most noteworthy facets of algorithms rest in the visible outputs and effects they produce (Mittelstadt et al., 2016; Hill, 2015; Bucher, 2018; Eubanks, 2019; and Andrejevic, 2019). The guiding premise here is that the most essential property of algorithms is not hidden in code, but rather in the process of their social enactment because algorithms only take action and yield effects once they are implemented and executed. Hill (2015), for instance, defines algorithms as devices empowered by given purposes and therefore establishes algorithms as active (as opposed to passive) entities with consequence. Echoing this notion, Bucher (2018) contends that the agency of algorithms emerges when they become empowered by social, political and ethical capacities. In other words, the only thing that matters is the outcome. Similarly, Eubanks (2018) affirms that the most important aspect to consider when studying algorithms is the consequences and effects they produce, or what algorithms do. Algorithmic literacy, or algorithm awareness, in this case, embodies critical knowledge and reflection about algorithmically performed tasks and their subsequent effects on the audiences who must contend with their outcomes.

Algorithms can be used to accomplish an extensive range of operational functionalities and, hence, tend to be categorized and studied according to their functional purposes and practical capacities (Latzer & Festic, 2019). Moreover, the defining features and implications of the technology varies greatly from one algorithm to another. As a result, most researchers tend to focus their investigations on specific types of algorithms (Hargittai & Micheli, 2019). This said, despite the myriad purposes for which algorithms are used (e.g., searching, observation/surveillance, prognosis/forecast, filtering, scoring, content production, and much more) a seemingly disproportionate number of studies focus on the algorithms used to personalize users' newsfeeds on social media platforms (Klawitter & Hargittai, 2018; DeVito et al., 2017; and Eslami et al., 2015), or to prioritize search engine query results (Hargittai & Micheli, 2019; Latzer & Festic, 2019; Mittelstadt et al., 2016; Noble, 2018). While the types of algorithms used in these contexts are noteworthy, they represent only a small fraction of today's algorithmic landscape (Hargittai & Micheli, 2019).

Nonetheless, one common facet of contemporary social science and humanities anchored research about algorithms is a concern with ethics. Indeed, concern with the ethical implications of algorithms has come to be widely viewed as a central component of algorithmic knowledge assemblages. To this end, a loose consensus appears to exist around the idea that algorithmic literacy, however defined, entails understanding the ethical implications of automated mathematical modeling systems (Bucher, 2018; O'Neil, 2016; Noble, 2018; Eubanks, 2018; Diakopoulos, 2019; Finn, 2017; Hasselberger, 2019; Oldridge, 2017; Mueller & Dhar, 2020; Dasgupta & Hill, 2020). Of particular interest in this regard is the decision-making power conferred to algorithmic modeling systems and their implications for human lives and society writ large. This view is summed up nicely by Koening (2020, p. 2) who writes, "algorithmic literacy focuses on the role that technology plays within a society: economically, politically, and socially."

A number of recent scandals illustrate the potential power, dangers, and flaws of algorithms and data harvesting procedures. The examples set out below highlighting some of the reasons why algorithmic literacy should be a concern for all.

1. *The Correctional Offender Management Profiling for Alternative Sanctions (COMPAS) scandal*. COMPAS is an algorithm used in state court systems across the United-States to predict individual recidivism risks for convicted felons. In 2016, a ProPublica investigation revealed, unequivocally, that COMPAS was biased against black defendants, with African Americans being almost twice as likely as Caucasians to receive a higher re-offence risk score. Northpointe, the company behind COMPAS, refuted all claims and refused to disclose details of its proprietary algorithm. Nonetheless, it continues to be used in the American legal. See, Corbett-Davies et al., (2016) and Mesa (2021).

2. *The Cambridge Analytica scandal.* Cambridge Analytica was a data analytics firm that unlawfully harvested millions of Facebook user profiles and used the collected information to manipulate voters' decisions by serving up false targeted ads to specific personality types during Donald Trump's 2016 U.S. Presidential election campaign. In 2018, on the heels of the ensuing scandal, the company closed it operations. See, Cadwalladr & Graham-Harrison (2018).

3. The case of Robert Julian-Borchak Williams. In 2018, Robert Julian-Borchak Williams was wrongfully arrested and accused of robbery in Detroit, Michigan after a facial recognition algorithm wrongfully matched him to a crime he did not commit. Mr. Williams was arrested,

held under a US$1,000 bond, and had to appear in court for an arraignment at his own personal expense. The case was later dismissed without prejudice. See, Hill (2020).

4. The SafeRent lawsuit, 2021. In May of 2021, a class-action lawsuit was filed in Massachusetts (U.S.A) by a black woman named Mary Louis against SafeRent Solutions on allegations of racial discrimination. SafeRent is an algorithmic tool used to generate risk scores for rental applicants based on their credit history and other credit-related information. The lawsuit alleges that the SafeRent tool discriminates against Black and Hispanic applicants and is therefore in violation of the *Fair Housing Act*; legislation prohibiting discrimination on the basis of race, disability, religion, or national origin in the United-States. The case is still before the court but could potentially become a landmark federal case regarding the use of AI technologies in the housing market. See, Johnson (2023) & Schoenberg (2023).

In these, and other similar, instances, one observes in the ever-growing body of research focusing on the ethical implications of algorithms and a link with advocacy for increasing levels of algorithmic literacy across societies (Bucher, 2018; O'Neil, 2016; Noble, 2018; Eubanks, 2018; Diakopoulos, 2019; Finn, 2017; Hasselberger, 2019; and Oldridge, 2017). The underlying motivation of much of this work is tied to a belief that algorithmic literacy "affords individuals the ability to question and critique representations of their world, as reflected to them via algorithmic output like search results" which, in turn, enables people to critically reflect upon the consequences engendered by algorithms on their own perceptions, practices, and online experiences (Cotter and Reisdorf 2020, p. 758).

Recent efforts at defining algorithmic literacy include Oldridge (2017) who suggests that this term involves being able to recognize when an algorithm is being used, to interpret what it is attempting to do, to understand the limitations of the technology, and to reflect on the effects it has on digital spaces and human lives. Like digital skills, it can be assumed that algorithmic literacy or knowledge about the topic of algorithms in a broader capacity involves sequential levels of understanding as opposed to definite states of awareness (van Deursen & van Dijk, 2010; Cotter & Reisdorf, 2020). This implies that algorithmic literacy involves differing levels of capacity rather than distinct conditions of knowing versus unknowing.

Other initiatives have sought to define algorithmic literacy by identifying specific abilities that foster higher levels of algorithmic knowledge: "understand what algorithms are […]; know where algorithms are deployed – today and in the future […]; Understand the intent/goals of those owning or deploying the algorithm […]; take control of your data and privacy […]; avoid dependency […]" (Mueller & Dhar, 2020; Kids Code Jeunesse (KCJ) & the Canadian Commission for UNESCO (CCUNESCO), 2020). These approaches suggest that acquiring such skills can help to protect the interests and well-being of those targeted and victimized by algorithmic systems. Yet, despite algorithms ostensibly being unavoidable, most people seemingly are, or remain, unaware of the functions of, and roles played by, algorithms in contemporary society.

This state of affairs points to the need to investigate both the ways in which algorithmic literacy is defined, along with what people know about algorithms and how they perceive and negotiate their daily interactions with algorithmic systems. With this in mind, my project was guided by two complementary research questions:

1. *From a socio-technical perspective, what are the key components of algorithmic literacy?*
2. *What is the level of algorithmic literacy among undergraduate students at the University of Ottawa?*

Prior to conducting my investigation, I hypothesized that levels of algorithmic literacy among my sample population would be somewhat low. I expected undergraduate students to have limited knowledge of algorithms beyond those associated with social media platforms and most likely only be able to convey surface-level reflections about how these mathematical engines shape and condition everyday life. I anticipated that the participants would demonstrate a higher level of reflectivity and greater general knowledge about social media related algorithms since I assumed most, if not all, would be avid social media users. As the discussion the next few chapters demonstrates, my initial assumption was not too far off the mark.

2.4 Conclusion

The discussion in this chapter has provided an overview of the main concepts at the core of my project: algorithmic bias, algorithm awareness and algorithmic literacy. I also examined the key issues and challenges associated with algorithms and algorithmic literacy. The discussion in the next chapter focuses on the first phase of my empirical investigation of algorithmic literacy; a systematic review of algorithmic literacy research published over the last 25 years in the fields of media and literary studies to ascertain whether any consensus exists around how to define this concept and the competencies with which it is associated.

Chapter 3 –Defining Algorithmic Literacy

The first step towards addressing the central research question guiding my project involved conceptualizing and defining algorithmic literacy. The discussion in this chapter sets out the findings from a systematic review algorithmic literacy research published over the last 25 years in the fields of media and literary studies. The chapter itself is divided into 4 sections. The first deals with the review methodology and specifies the approaches that were used to organize, structure, and perform the systematic review of the literature. In section two, I set out how the evidence sample was collated, paralleled, and analyzed to produce initial observations and findings regarding how algorithmic literacy is defined. The third section examines the relationships between the definitions and concepts identified along with some of the commonalities and recurring trends found in the sample. Section 4 concludes the chapter.

3.1 Systematic Review of the Literature About Algorithmic Literacy

A systematic review of literature is a technique used to identify, select, and appraise a body of literature following predetermined, explicit procedures to collect and synthesize the findings of relevant studies in an unbiased manner (Klassen, Jadad, & Moher, 1998; Synder, 2019). When used as a methodological tool, a systematic review of literature summarises and integrates empirical findings from a large number of studies, answers research questions, and provides a foundation for knowledge advancement by presenting the state-of-the-art understanding regarding a given subject (Khan, Ter Riet, Glanville, Sowden, and Kleijnen, 2003; Pejić-Bach & Cerpa, 2019; Snyder, 2019). Quantitative systematic literature review methods have a long history in evidence-based disciplines such as medicine and nursing (McCarthy, 2008), and have increasingly been applied within the social-sciences and humanities (Xiao & Watson, 2019) as a means of summarising "existing findings about a well-defined topic in a thorough, focused, replicable, and unbiased way, with the aim of responding to relevant pre-defined questions and drawing well-supported, unbiased and more general conclusions than those obtained from individual research studies” (Pejić-Bach & Cerpa, 2019, p. 1).

The common approach to conducting systematic reviews of literature, involves synthesizing and explaining research findings from multiple studies in a narrative form (Rodgers et al., 2009; Popay et al., 2006; Mays et al., 2005). These reviews often are perceived as the middle ground between qualitative and quantitative review approaches insofar as they encompass simple methods for integrating findings from multiple studies and allow for a certain level of information interpretation and integration (Pope et al., 2007; Rodgers et al., 2009). The versatility of narrative syntheses rests in the extent to which they enable one to draw from qualitative and quantitative data, statistical evidence, and other types of research and non-research materials to synthesize, merge or generate new theories about the investigated topic (Mays et al., 2005; Rodgers et al., 2009).

This thesis involved conducting a narrative synthesis of studies dealing with algorithmic literacy. The aim of this exercise was to identify:

1. If there exists a set definition of algorithmic literacy; and
2. the main themes revolving around this concept across a wide range of academic and non-academic sources.

In conducting this review, I followed the approach set out by Popay et al., (2006). As noted by these authors, a systematic review of literature is not a linear process. Rather, it involves continual back and forth movement between and within each stage of the review process. In the case of my thesis, this process was divided into five phases and, in accord with Popay et al.,’s (2006) recommendations the review is organized and presented in a linear fashion

3.1.1 Identifying the review focus and search for available evidence

The initial phase of the systematic review process involved a preliminary scoping exercise that began on the SCOPUS, ProQuest, Communication Source, Academic search complete, SpringerLink and Google Scholar databases. This search relied on the use of three key words relating to algorithmic literacy: Algorithmic literacy; Algorithm awareness; Algorithmic knowledge. This first exercise was performed to assess the volume of works available about the given topic. It generated hundreds of results across the databases. The returned works were then loosely triaged based on their perceived relevance to, and perceived relationship with algorithmic literacy.

My informal analysis of the returned results suggested that, despite frequently being mentioned, there seemingly is no specific, or widely accepted, definition of the term 'algorithmic literacy.' Instead, this concept appears to be defined in relation to, and/or in tandem with, other types of literacies broadly involving similar elements – e.g., digital literacy, information literacy, data literacy, computer literacy, and critical literacy (Gillespie & Seaver, 2016; Pfeffer & Mayer, 2019; Moats & Seaver, 2019; Bakke, 2020; Koening, 2020). Put simply, algorithmic literacy remains an abstract concept, with researchers tending to advance their own understanding of what this competence encompasses in relation to their research objectives (O'Neil, 2016; Oldridge, 2017; Bucher, 2018; Eubanks, 2018; Hasselberger, 2019; Glotfelter, 2019; Bakke, 2020; Dasgupta & Hill, 2020; Mueller & Dhar, 2020).

Further complicating matters, studies of algorithmic literacy originate from various disciplines including, computer science, engineering, mathematics, social sciences, education, and communications. The multi-faceted nature of this topic and the myriad theoretical perspectives through which it is studied has perpetuated a dichotomous view of the concept wherein some define algorithmic literacy in an instrumental manner that focuses foremost on computational design and skills whereas others employ a broader socio-technical understanding[11] that focuses attention on the ethics, politics, and power-issues stemming from the context in which algorithmic system applications are designed, implemented, and used (Citron & Pasquale 2014; Pasquale, 2015; Hill, 2015; Mittelstadt et al., 2016; Bucher, 2018; Latzer & Festic, 2019; Pangrazio and Selwyn 2019; Bakke, 2020; Raffaghelli & Stewart, 2020).

This informal exercise combined with the hands-on assistance of a research librarian from the University of Ottawa[12] helped me to zero-in on the narrative synthesis approach to synthesize the available evidence. Based on the preliminary observations set out above and bearing in mind both the breadth of the available materials[13] as well as the central goal of my thesis, I elected to proceed with a review of different iterations of algorithmic literacy from a social sciences and humanities. This meant disregarding the ways in which algorithmic literacy is dealt with in mathematics, computer sciences, and software engineering.

3.1.2 Identifying studies to include in the systematic review

The second phase of the synthesis process focused on establishing and refining the main question guiding the review in accord with the information gathered during the first phase. The objective here was to set out a review question that could be relied upon to guide my interrogation in a clear and precise manner and, in so doing, shape the search strategy and guide decisions about the

[11] Socio-technical perspectives are characterised by analyses aimed at understanding and critically reflecting on the relationships between people and technologies and the social concerns associated with technological innovation. Works in this field investigate the performative and normative aspects of technological practices (such as data sciences) and systematically seek to challenge the legal, ethical and social issues incorporated in such disciplines. See, for example, Pfeffer & Mayer (2019), Gillespie & Seaver (2016), and Moats & Seaver (2019).

[12] My thanks to Tea Rokolj, Libarian at the University of Ottawa,for her help and assistance in defining and establishing the most appropriate approach to conducting the systematic review of literature.

[13] The extensive body of research produced about algorithmic literacy made it unrealistic for me to undertake a systematic review of the literature encompassing studies from all research fields and backgrounds.

inclusion and exclusion criteria for the studies considered (Mays et al., 2005). The central review question developed asked: *From a socio-technical perspective, what are the key components of algorithmic literacy?*

The next step involved deciding upon the inclusion and exclusion criteria to be used to maximise the relevancy of the database search results generated. Based on the conclusions reached in the scoping stage of the review (i.e., no agreed definition of algorithmic literacy, and bifurcated view of the concept), I opted to make inclusion in the official review sample contingent upon the returned articles meeting the criteria listed in Table 3.1. To ensure that the research strategy used was transparent and systematic throughout, I followed the methodology adopted by Williams et al. (2018) to perform a structured data extraction.

Table 3.1: Inclusion Criteria

Level 1	**Level 2**
Included if:	*Included if:*
• Research studies that present theoretical or empirical methods and results • Peer-reviewed articles published between February 1996 and March 2021 • Published in English language[14] • Full text must be retrievable	• Examined algorithmic literacy (or a related term) by defining/interpreting the concept (or a related notion) from a social sciences or humanities perspective • Defined/discussed/studied algorithms from a socio-technical perspective • Focus/interest was put on what algorithms do and their consequences rather than how they do it.

With the inclusion criteria in place, I proceeded with the formal keyword searches search. To begin, I limited my search strategy to the Academic Search Complete, ERIC, ProQuest, and SCOPUS academic databases. The keyword searches of the chosen databases returned 169

[14] Given the complexity of the subject matter, the search results were limited to works published in English so as to avoid the need to translate any returned results.

academic articles (see Table 3.2). To assist in this process, I used DistillerSR[15] to facilitate the collection, management, sorting, and assessment of the peer-reviewed articles included in the review process. After removing duplicates and non-English language studies, 138 academic articles remained.

Table 3.2: Returned results per database

	Academic Search Complete	ERIC	ProQuest	SCOPUS	Total
"Algorithmic literacy"	5	0	8	11	24
Algorithmic + literacy	8	18	0	64	90
Algorithmic NEAR/20 literacy	0	0	55	0	55
Total	13	18	63	75	**169**
After duplicates and non-English works removed					**138**

I then conducted a Google search[16] using the keyword 'algorithmic literacy' to see if this might turn up potentially relevant non-academic publications and documents not be listed in the latter databases. Given the rapid pace at which new content appears online, only items published between February 2010 and March 2021 were accepted from the Google results. This shorter timeframe was used to ensure that identified documents provided relevant and updated information about algorithmic literacy. The Google search generated some 829,000 returns of which I examined the first 40 links (approximately the first four pages), sorting them by perceived relevance, and type (i.e., academic paper, conference proceedings, independent initiative,

[15] See, https://www.evidencepartners.com/products/distillersr-systematic-review-software

[16] The google search was conducted while logged into my personal Google account. Prior to conducting the official Google search, I performed a key word search of the term 'algorithmic literacy' using Google's incognito mode to compare whether the results returned might be substantially different from those generated when logged into my personal account. The results returned on the first three pages were the same except for two documents. As such, I opted to perform the official Google search while being logged into my personal account. It also merits noting that I deliberately opted not to use Google Scholar to conduct my search because I wanted the search to include any possibly relevant non-academic publications.

academic blog, and news publication). This exercise identified 15 documents that were added to my sample. These 15 records from the Google search plus the 138 from the database search brought my sample size to 153 documents.

The 153 articles were then incorporated into the level 1 screening process. This involved reading each article's title and abstract to assess whether it discussed topics relating to algorithmic literacy. From there, I posed one question:

> *Should this reference continue to the next level of screening? If yes, include in the sample. If no, exclude from the sample. If not sure, categorise as 'conflict.'.*

This first stage of screening resulted in 100 articles being removed from the sample on the grounds that they either discussed topics that were not directly related to algorithmic literacy[17] or examined algorithmic literacy from a mathematical, or natural sciences standpoint. The references catalogued as 'conflict' automatically progressed to the level 2 screening process to be assessed for full-text eligibility. The remaining 53 articles were then incorporated into a full-text eligibility assessment.

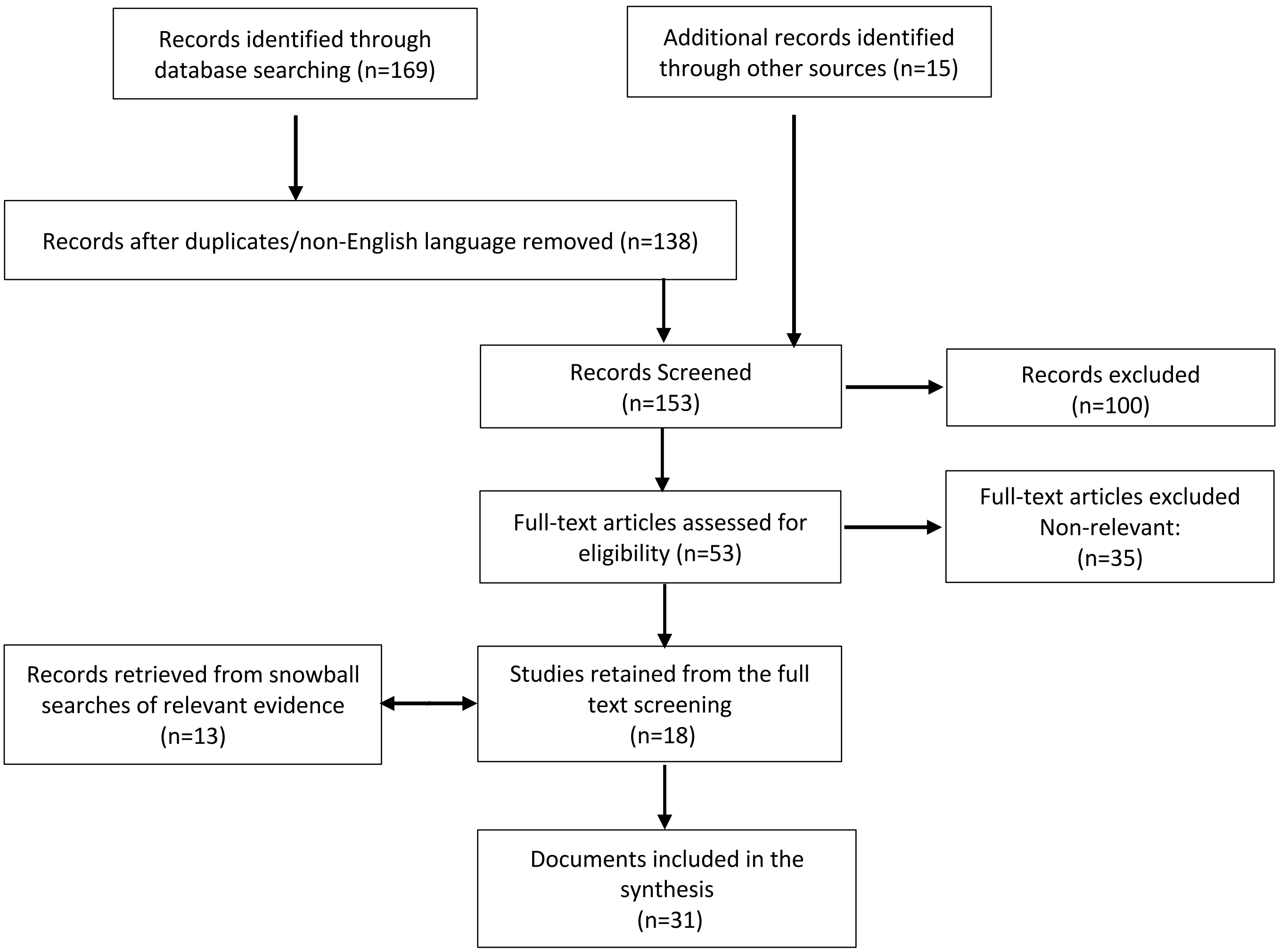
This second level of screening comprised two stages. First, I read each of the 53 articles in full and re-assessed their eligibility for inclusion in my sample in accord with the inclusion criteria set out in Table 3.1. Upon completion of this exercise, 18 articles were retained. Second, I then went back and conducted snowball searches[18] using the bibliographies and reference lists of these 53 articles to identify other potentially relevant documents that may, as of yet, have been overlooked. In order to be added to the sample, the documents identified using the snowball

[17] Despite textually mentioning the searched keyword, the main subject matter of a handful of articles did not pertain to algorithmic literacy and, as such, was deemed not relevant for the purposes of this project.

[18] The snowball method involves using a key document as a starting point and consulting its bibliography to find other documents of relevance to a given research topic. Snowball searches consist of tracking down references and citations to find other related documents.

method needed to be cited in at least two of the documents from the 18 I had retained for my sample during the first stage. Thirteen documents were identified in this manner, bring my final sample size to 31 documents: 24 academic articles, and 7 non-academic publications (see, Appendixes 1 & 2). Figure 3.1 provides a schematic representation of the search process outlined above.

Figure 3.1 PRISMA Flowchart



3.2 Synthesis of the results

The synthesis stage was the central component of the review process. It involved integrating the findings collected from the 31 items comprising my sample. The information extracted from the sampled articles was mainly comprised of definitions and interpretations of algorithmic literacy, or any information that would allow a better understanding of what the concept means, entails and/or encompasses.

In line with the approach proposed by Popay et al., (2006), I divided the synthesis phase into three stages. The first was rooted in a scoping and textual description process aimed at producing an in-depth analysis of the information presented in the documents comprising my sample. This involved my reading each of the 31 documents twice, identifying the main idea(s) conveyed within each and the writing of a short – one to two sentence – summary of these ideas. I organized the list of articles and their respective summaries by hand in a notebook because I considered it made it easier for me to refer to each summary when needed and this gave me the opportunity to organise each section as I desired. The goal of this exercise was to map out the central idea discussed in each document relative to my review topic (i.e., *From a socio-technical perspective, what are the key components of algorithmic literacy?*). This exercise also facilitated the preliminary identification of overarching recurring topics and the grouping of texts into smaller clusters (see Table 3.3).

Despite the variations between articles regarding the specific meaning of algorithmic literacy and/or what exactly it entails, the concept of literacy itself was broadly found to be used and defined analogously in each document in the sample. Specifically, the concept of literacy advanced in the sampled works aligned with Cope and Kalantzis' (2009, p. 175) claim that literacy does not necessarily involve acquiring implicit technical skills but rather, aims to create a "kind of person, an active designer of meaning, with a sensibility open to differences, change and innovation." To this end, within the sampled articles one observed an onus being placed on equating literacy with the development of critical thinking capacities and understandings wherein meaning making is seen as an active, transformative, reflexive process. In addition, the

Table 3.3: Excerpt from notebook notes

Author	Title	Main Idea	Summary
Rob Kitchin (2007)	*Thinking critically about and researching algorithms*	Acquiring algorithmic knowledge	Knowing algorithms equates understanding them critically / knowing what they do in the world and how it affects people, society, and the world.
Erin Klawitter & Eszter Hargittai (2017)	*It's Like Learning a Whole Other Language": The Role of Algorithmic Skills in the Curation of Creative Goods*	Investigating algorithmic skills & algorithmic knowledge	Research study aimed at investigating the algorithmic skills (and knowledge) of creative entrepreneurs who are heavily impacted by algorithms due to their line of work (selling creative goods online).
Kelley Cotter & Bianca C. Reisdorf (2019)	*Algorithmic Knowledge Gaps: A New Dimension of (Digital) Inequality*	Information mediation.	Explores algorithmic issues (mainly issues related to content mediation) and algorithmic awareness, mostly in relation to search engines algorithms.
Martijn van Otterlo (2014)	*Automated experimentation in Walden 3.0: Article The next step in profiling, predicting, control and surveillance*	Algorithms and issues of privacy	Analysis of how algorithms (especially AI algorithms & prediction algorithms) are engendering privacy issues for users (profiling).
Annemaree Lloyd (2019)	*Chasing Frankenstein's monster: information literacy in the black box society*	Algorithms and their ethical issues	Study that dives into the ethical issues that have been associated with algorithms. Lloyd overviews & presents several ethical concerns from a variety of stand points to advocate for the need to increase reflexivity and information literacy when dealing with algorithms.

understanding of literacy in these articles appeared to parallel socio-technical rooted perspectives regarding the conceptualization of digital literacies more broadly. Although five documents detailed specific aptitudes associated with understanding matters relating to the use and application of algorithms across various platforms and contexts, algorithmic literacy definitions were always centered around acquiring knowledge about how algorithms work as opposed to linking algorithmic literacy to technical proficiencies and skills such as coding and programming. This made it easier for me to focus my efforts on identifying the main components of algorithmic literacy insofar as seeing that the concept of literacy was approached homogenously across my evidence sample, I was able to mainly focus my efforts on the specificities of algorithmic literacy rather than having to tend to various interpretations of literacy itself, and algorithmic literacy.

Eighteen of 31 documents in the sample defined algorithmic literacy in relation to a particular platform (n=9) or context (n=9). For example, Hargittai & Klawitter (2018), Cotter & Reisdorf (2020), and Bakke (2020) outlined explicit capacities and reflections associated with knowing and understanding specific search engine algorithms, and Eslami & al. (2015), and Rader & Gray (2015) focused on social media algorithms. Hobbs (2020) discussed issues, practices, understandings, and opportunities specifically associated with (and limited to the context of) personalization algorithms, while Mittelstadt et al., (2016) focused on similar elements but in relation to algorithmic decision-making. Given my desire to move beyond definitions that were bound to specific platforms or contexts, I then chose to perform a thematic analysis aimed at identifying the central theme(s) in each of the articles comprising the sample.

The thematic analysis followed the approach outlined by Braun & Clark (2008) who advocated for the use of this technique in qualitative research endeavors both within and outside the field of psychology. The authors detailed how performing a thematic analysis enables researchers to identify, analyze and report patterns and themes within a qualitative data set, and facilitates the interpretation of various aspects of the topic at hand. Furthermore, Braun & Clark (2008) provide clear guidelines on how to conduct a thematic analysis. Their technique involves six steps: familiarizing oneself with one’s data; generating initial codes; searching for themes; reviewing themes; defining and naming themes; and producing the report.

Having previously examined the sampled articles, I began by highlighting the significant sentences and excerpts found in each text using a personalized color-coding scheme that involved highlighting central ideas in yellow, recurring keywords in orange, and algorithmic literacy definitions in blue. This exercise enabled me to catalogue and organize the different contributions advanced in the sampled articles by identifying recurrent themes. Once this first step was completed, I moved to extracting the main ideas conveyed across the documents and organizing these ideas into meaningful groups. This involved deriving initial codes from the highlighted citations and grouping them together to create lists of similar keywords and themes (see Table 3.4).

Table 3.4: Example of keyword and theme categorization

Reference	Keywords	Themes	Macro theme
Dowdeswell, T. L., & Goltz, N. (2020). The clash of empires: Regulating technological threats to civil society. Information and Communications Technology Law, 29(2), 194–217. Scopus.	1. Inequalities 2. Bias and discrimination 3. Surveillance and data collection 4. Social issues & dilemmas caused by algorithms 5. Transparency	1. Algorithm & issues 2. Algorithm & ethics 3. Algorithmic injustice	1. Algorithm issues
Hobbs, R. (2020). Propaganda in an Age of Algorithmic Personalization: Expanding Literacy Research and Practice. Reading Research Quarterly, 55(3), 521–533. Academic Search Complete.	1. Data harvesting and surveillance 2. Algorithmic personalization can be conceptually understood as a new type of manipulation 3. transparency, equity, and fairness are needed to prevent digital bias and discrimination	1. Algorithmic personalization 2. Personalization instigating issues 3. Algorithms and their applications/use	1. Algorithm functionality

Table 3.4: Example of keyword and theme categorization (cont'd)

Koenig, A. (2020). The Algorithms Know Me and I Know Them: Using Student Journals to Uncover Algorithmic Literacy Awareness. Computers and Composition, 58, 102611.	1. Theoretical approach to algorithmic literacy 2. Digital literacy 3. Role that technology plays within a society 4. Awareness 5. Understand how students engage with algorithmic platforms 6. Reflect on their own awareness 7. Technological literacy practices	1. Algorithmic awareness/knowledge 2. Algorithms and practices 3. Investigating student's algorithmic literacy 4. Defining algorithmic literacy 5. Algorithmic literacy practices 6. Framework to study algorithmic literacy 7. Algorithms and their applications/use	1. Algorithm knowledge
Lloyd, A. (2019). Chasing Frankenstein's monster: Information literacy in the black box society. Journal of Documentation, 75(6), 1475–1485. Academic Search Complete.	1. Transparency 2. Black box 3. Bias, trust, credibility, opacity, diversity, and social justice, commensurability (how algorithms interact with us to shape and reshape knowledge and agency) and performativity.	1. Issues of representation, knowledge bias, power 2. Issues of marginalisation; social consequences of algorithmic culture on the fabric of social life	1. Algorithm issues
Willson, M. (2017). Algorithms (and the) every day. Information, Communication & Society, 20(1), 137–150.	1. Agency 2. Power 3. Sort, filter, and curate 4. Human to algorithm relationship (power dynamic) 5. Algorithms as everyday practices 6. Shaping of everyday practices 7. Effect	1. Algorithmic power 2. Algorithmic personalization 3. Algorithms and their related practices	1. Algorithm functionality

Three macro-level themes were initially identified as being indicative of the contents of the 31 articles comprising the sample: algorithm issues, algorithm knowledge, and functionality. Yet, these macro-level themes were too vague and all-encompassing. As such, I refined the categories and clusters by reviewing the recorded lists of keywords, re-examining the highlighted text, and reorganizing the keywords and themes by subject matter so as to narrow the scope of each category to form more specific groupings.

For example, Michele Willson's publication which I had initially categorized under the macro theme of algorithm functionality (shown in table 3.4) was grouped among a new cluster titled algorithmic power and governance which regrouped publications containing keywords such as *power, agency, governance, effect, incidence, and control*. This search for sub-categories within the previously established groupings combined with the reassembling the relevant keywords resulted in my identifying new themes. For instance, keywords such as *surveillance*, *data collection*, *security of personal information, data harvesting,* and *tracking and predicting users' behavior*, which had initially all be categorized under the theme of algorithm issues were now regrouped under the theme of Privacy. From this exercise, five predominant themes were identified (see Table 3.5): functionality, power and governance, personalization, ethics, and privacy.

Table 3.5: Algorithmic Literacy Definition Themes

Theme	Topic	Related notions
Functionality	• What algorithms are; • How they work; • Why they are used/ what they are used for; • Where they are used	• Types of algorithms (Machine-learning algorithms; chat bots; Artificial intelligence) • Types of functions (Predict, suggest, curate, generate, filter, prioritize, classify, extract, etc.) • Where do we encounter algorithms? • How do we engage with algorithms? • Algorithms and the transformation of practices/labour (i.e., journalism) • Automated; automatic, & autonomous
Power/ Governance	• Algorithms construct & implement regimes of power & knowledge through their capacity to influence behaviours, consumption habits, information retrieval & democracy (political persuasion). • Algorithms are performative entities that have influence & consequence • How do algorithms exert their power inside and outside digital spaces? • How do algorithms exert their power on my life?	• Agency • Decision-making • Access • Empower, entertain & enlighten • Algorithmic regulation/policy • Power over what I see, what I buy • Political influence
Personalization	• What is algorithmic personalization? • How does it affect online experiences? • Algorithmic personalization occurs through data collection processes: personal data is gathered through online interactions, use, navigation, preferences, and used to generate targeted ads, suggest content, curate news feed, etc. • Where/why does it occur? • Who does it affect?	• Content mediation & curation on social media, search engines, online shopping, etc. • 'Filter bubbles'; echo chambers; targeted ads • Interdependency with algorithms • Mutual process • 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 • Algorithms learn from your behaviour, can limit the options made available to you online, and influence your choices. • Protect against the risks and potential harms of personalized propaganda while emphasising empowerment with a nuanced appreciation of how algorithmic personalization and propaganda may benefit individuals and societies.

Table 3.5: Algorithmic Literacy Definition Themes cont'd

Ethics	• Ethical challenges wrought by algorithms, algorithmic bias. • How does algorithmic bias occur? • How do algorithms reflect and reinforce bias? • How can algorithms mitigate bias? • Algorithms as "black boxes"	• Embedded/encoded bias; algorithmic accountability; Algorithmic transparency; algorithmic fairness • Algorithmic decision-making & it's effect on human lives • Algorithmic issues; algorithms and discrimination, racism, marginalization; implementation of algorithmic process in social programs. • Reflexivity • Machine-learning and bias • Differential Access to goods and services • Digital divides
Privacy	• Algorithms & their impact on online privacy & personal information security • Algorithms and their use of personal data • When does data collection occur? • How does algorithmic data collection affect me? • Why is data privacy important?	• Susceptibility to surveillance and data collection • Big data; data capitalism; data harvesting, Data-brokerage (USA) • Algorithmic models/profiling (Profiles induce categories, or sub-groups, to which people can belong (to a certain degree) • Commodification of data; personal data being bought, sold, and used

All 31 works in the sample discussed, or at least mentioned, the functional properties of algorithms. Indeed, the broad technical features of algorithmic systems and the description of their key processes are incorporated in the articles to explain and define algorithms and/or algorithmic literacy. Thus, the first theme identified was termed functionality. It refers to and includes broad understandings about the ways in which algorithms work, and the functional purposes they serve. More specifically, this theme encompasses knowledge of what algorithms are, the intent behind the technology, (see: Mueller & Dhar, 2020), how algorithms work (see: Hargittai et al., 2020), where they are used (See: Bakke, 2020; and Hobbs, 2020), types of algorithms (See: Dowdeswell & Goltz, 2020; and Willson, 2017), and the tasks algorithms can perform (see: Beer, 2017).

The second recurrent theme was power and governance. It was present in 23 of the 31 documents comprising the sample. It largely encompasses all the other themes identified but focuses specifically on the performativity of algorithms and the power and knowledge regimes they implement. Put simply, this theme encompasses the consequences and influence algorithms have over behaviors, consumption habits, democracy, and access to information. The theme of power and governance in this context is rooted in reflections about the ways in which power operates through algorithms, how algorithms are built into organisational structures, and how algorithms inherently become part of decisions, choices, and human lives (Beer, 2017). Lloyd (2019, p. 1483), for example, suggests that algorithms should be considered as practices with influence other aspects of social life, and that commensurability – or "how algorithms interact with us to shape and reshape knowledge and agency" – as well as performativity, should be integrated among other concepts into current approaches to literacy whether algorithmic or other. Such contentions align with those of Kitchin (2017, p.19), who asserts that by introducing systems of power and knowledge, algorithms can be "used to seduce, coerce, discipline, regulate and control:

to guide and reshape how people, animals and objects interact with and pass-through various systems." This extends to understanding the authority algorithms might have over feelings, emotions, and friendships through social media (see, Bucher, 2018; Willson, 2017).

Personalization was the third theme to emerge. It was present in 22 of the 31 articles in the sample. Algorithmic personalization is related to functionality insofar as it encompasses certain tasks performed by an algorithm (e.g., filtering). However, within the context of this thesis, it is understood as referring to every concept, notion, challenge, or issue relating to the role assumed by algorithms in shaping, mediating, and manipulating the display of – and access to – online information, entertainment and other types of content (see Hobbs, 2020). Related notions include filter and/or preference bubbles and echo chambers, that are documented as being the by-product of algorithmic personalization practices (Kids Code Jeunesse (KCJ) & the Canadian Commission for UNESCO (CCUNESCO), 2020; Reisdorf & Blank, 2021). Hence, personalization and its related concepts – particularly in relation to awareness of algorithmic interference in online spaces, experiences, and practices – are inherently part of algorithmic literacy definitions.

The fourth recurrent theme pertains to the ethical implications of algorithms. In this instance, ethics refers to the effects algorithms have on human lives, the moral dilemmas associated with their implementation, and/or the consequences they engender on society writ large. Nearly half of the documents in the sample (n=14) discussed the importance of acquiring at least basic knowledge about the ethical challenges, implications, and opportunities wrought by algorithmic systems. Ethics in this context broadly implicates learning and critically reflecting on the relationship between algorithms and concepts such as bias, trust, fairness, neutrality, credibility, transparency, diversity, accountability, and social justice (see, Lloyd, 2019; Tsamados et al., 2020; Cotter & Reisdorf, 2020; Bakke, 2020; Hobbs, 2020; Koening, 2020). Yet, ethics also encompasses notions relating to the potential ethical benefits afforded by algorithms in terms of improving the consistency, replicability, and impartiality of algorithmically mediated processes (Rainie & Anderson, 2017; Hobbs, 2020).

The fifth recurrent theme was privacy. It was present in 12 of the documents included in my sample. Particularly noteworthy in this regard was the intersection of algorithms and data privacy, and the rapport between data, algorithms, and the impacts of algorithmic systems on privacy, personal information security, and the processes of surveillance and data collection (see notably, Dowdeswell & Goltz, 2020). Privacy in this context also pertains to recognizing that data collection processes are found at the base of nearly every algorithm encountered, being mindful of the implications such practices hold, and knowing how to use, protect, and take control of your personal data and online privacy (see, Van Otterlo, 2014; Head et al., 2019; Lloyd, 2019; Mueller & Dhar, 2020). It merits noting that whereas manifestations of personalization within the sampled documents tended to focus on notions and challenges relating to content mediation, curation, targeted advertisement, filter bubbles, and propaganda, the privacy discussions focused on data collection processes, big data, algorithmic profiling, personal information security, data harvesting, predictive modeling, profiling, data capitalism, and data surveillance (see for example: Mittelstadt et al., 2016; Bucher, 2018; Hobbs, 2020). To this end, four articles in the sample advanced the idea that algorithmic literacy and big data literacy intersect on matters concerning data privacy and data collection (see, D'ignazio and Bhargava, 2015; Reisdorf & Blank, 2021; Rainie & Anderson, 2017; Lloyd, 2019).

For example, D'ignazio and Bhargava (2015) posit that big data awareness involves being able to identify when and where details about one's actions and interactions are being collected, and understanding the role assumed by algorithms for data collection, manipulation, and pattern recognition purposes. Building on this idea, Reisdorf & Blank (2021) suggest that the concepts of big data literacy and algorithmic literacy both focus on the same thing – that is, understanding how big data and algorithms affect the online experiences of Internet users.

The majority of the documents in my sample (23 out of 31) defined or discussed algorithmic literacy by observing and analyzing the power algorithms yield over people, processes, and systems. The underlying idea spanning these documents was that improving levels of algorithmic literacy would enable people to more effectively recognize the moral stakes associated with the development, implementation, and use of algorithms, and to critically reflect on the consequences algorithms engender on their own perceptions, practices, and online experiences.

What emerges, then, from my analysis of the sampled articles is an understanding of algorithmic literacy as a multifaceted concept that encompasses several different components and capabilities. As such, it appears there can be 'no one size fits all' definition of this concept not least because, as my analysis suggests, algorithmic literacy is defined by – and in relation to – considerations of functionality, power and governance, personalization, ethics, and privacy. Consequently, it seems reasonable to conclude that assessments of algorithmic literacy need to investigate knowledge bases of individuals in relation to each of these five factors.

3.3 Examining relationships among ideas within the sampled documents

Whereas the first phase of my review sought to identify and compile contributions in the sampled articles advancing the understanding(s) of algorithmic literacy, the second phase focused examining the nature of the relationships among the ideas both within and across the sampled documents.

One of the first observations I made was what that among these documents, those focusing on social media algorithms (n=6) mainly dealt with matters relating to personalization (i.e: Bucher, 2018; Rader & Gray 2015; Eslami et al., 2015; Devito et al., 2017), whereas those dealing with search engine and/or internet browsing algorithms (n=7) primarily engaged with issues of power/governance (see for example, Hobbs, 2020; Cotter & Reisdorf, 2020; Dowdeswell & Goltz, 2020; Bakke, 2020). Nonetheless, these considerations overlap insofar as personalization closely relates to notions of power and governance. This is in no small measure tied to the fact that, by controlling what a user sees or finds while navigating on Facebook, searching on Google, engaging with other social media platforms, algorithmic curation and prioritization introduces systems of knowledge and power (Beer, 2019; Dowdeswell & Goltz, 2020). What is more, personalization also is linked to privacy issues, with personalization occurring as a direct result of personal data being collected and modeled by machine-learning algorithms (Willson, 2017; Devito et al., 2017; Klawitter & Hargittai, 2018).

To further illustrate the connexions between the different themes identified in section 3.2, I used the conceptual mapping described by Popay et al.'s (2006) in their discussion of narrative syntheses. According to these authors, developing conceptual maps can make transparent the logic behind subgroup analysis/investigation (see, section 3.2). Conceptual mapping also affords structure to the synthesis by providing a clear representation of the ways in which ideas and issues are linked.

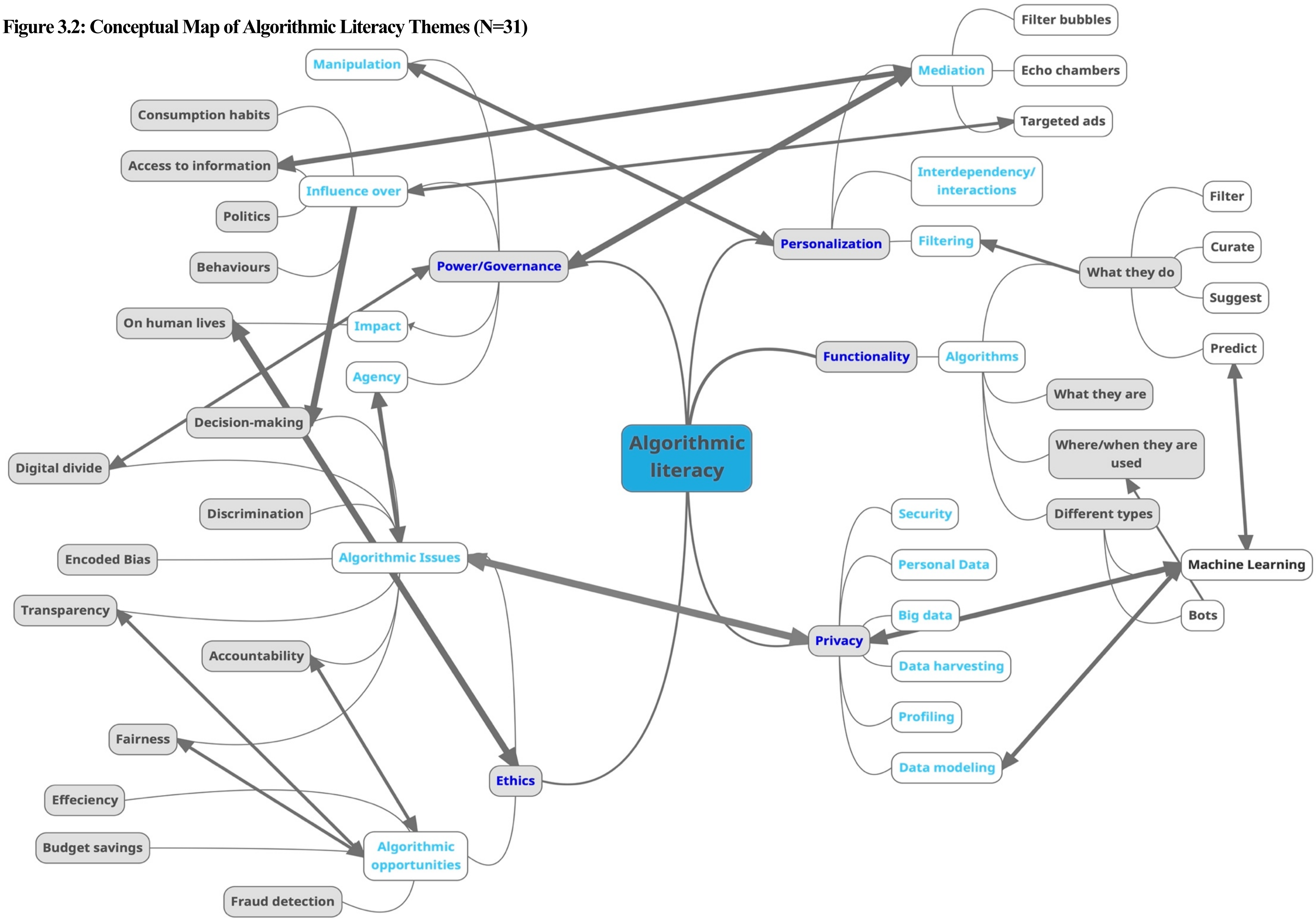
The first step involved setting out the core of my map – algorithmic literacy – and linking the five themes that emerged from the thematic analysis. Using the keyword groupings and clusters prepared in the previous stage, I collated and coded the first subset category within each theme. This entailed reviewing the components of each theme (that is the keywords, themes, highlighted sentences, and the short descriptions) and identifying new clusters within them. For example, seeing that elements regrouped under algorithm ethics either discussed algorithmic issues or algorithmic opportunities, I branched out the first sub-categories under this theme accordingly.

I then repeated the process focusing, this time, on extracting the very precise themes encompassed in the refined data sets. This exercise resulted in the identification of several narrow themes falling under the scope of each of the five overarching themes identified and thus provided more clarity regarding what they each entailed. Once all the narrow themes were categorized and forked to their respective subsets, I incorporated arrows to illustrate the relationships between each one. When a clear pattern or relationship between two themes was established in the documents reviewed and sustained across the material evidence (i.e.: two or more themes being related in more than 2 documents comprised in the evidence sample), the distinctive subgroups were linked together by means of an arrow.

For example, 19 of the 23 articles discussing algorithmic power and governance also touched upon algorithmic mediation (and personalization) and upheld the idea that the mediating role assumed by algorithms is a vector of algorithmic power and governance (see for example: Powers, 2017; Beer, 2019; Lloyd, 2019; and Dowdeswell & Goltz, 2020). As such, a thick arrow was used to illustrate the strong intersection (and frequent recurrence of parallels) between both subdivisions. The width of the arrows incorporated in the conceptual map vary according to the frequency of occurrence exhibited in the data sample. Three different arrow widths can be found in the map: the thickest arrows designate items that were often related together (in more than 5 documents) across the evidence sample (for example: *Privacy* and *Algorithmic Issues)*, bold arrows indicate themes that were occasionally (in 3 - 4 documents) linked together (*Personalization* to *Manipulation)*, and thinner arrows illustrate themes that were related together a few times (1 – 2 documents) (see: *Influence over* and *Targeted ads*).

Hence, the conceptual map presented in Figure 3.2 illustrates the relationships identified between the central themes and concepts that appeared to define algorithmic literacy within the 31 articles comprising my sample.

Figure 3.2: Conceptual Map of Algorithmic Literacy Themes (N=31)



3.4 <u>Conclusions</u>

In discussion in this chapter set out the manner in which I proceeded to conduct a systematic review of the literature pertaining the topic of algorithmic literacy in order to ascertain a clear, all-encompassing definition of what this concept entails. Although admittedly not generalizable, the initial findings of my investigation suggest there is no straightforward or ‘one size fits all’ definition of algorithmic literacy. This said, my analysis identified the presence of five themes that appear, within my sample at least, to be central to the concept of algorithmic literacy: Algorithmic functionality, power & governance, personalization, ethics, and privacy. The identification of these themes seemingly lends credence to the notion that it may well make more sense to speak of algorithmic literacies (plural) than algorithmic literacy. With this in mind, the discussion in the next chapter sets out how the five latter themes were used to inform the conducting of a series of focus group discussions with undergraduate students from the University of Ottawa aimed at assessing the level of algorithmic literacy present among them.

Chapter 4 – Investigating algorithmic literacy in real life

The reader will recall that the central research guiding my project is: *What is the level of algorithmic literacy among a sample of undergraduate students at the University of Ottawa?* Having set out how algorithmic literacy has been conceptualized throughout the past 25 years in the fields of media and literary studies, I turn my attention in this chapter to the levels of algorithmic literacy present among a sample of undergraduate students enrolled at the University of Ottawa, Canada. For this second phase of my project, my investigation entailed conducting focus group discussions structured around a series of questions that were formulated in accord with the five themes identified as being central to the concept of algorithmic literacy: Algorithmic functionality, power & governance, personalization, ethics, and privacy. The discussion in this chapter is divided into four sections. The first begins by setting out the conceptual framework and methodology used to organize and structure focus group discussions. Section 2 is dedicated to reporting on the information gathered from the focus group sessions. The discussion in section three explores implications of the findings that emerged from the focus group sessions. Section four concludes.

4.1 Phase 2 methodology

The second phase of my project involved conducting four focus group discussions, each lasting approximately 75 minutes in duration. The original plan was for each group to be comprised of six undergraduate students (N = 24). The decision to proceed with focus groups of this size (n = 6) was in keeping with recognised best practice for conducting focus group discussions (see, Baumgartner, Strong, & Hensley, 2002; Bernard, 1995; Johnson & Christensen, 2004; Krueger, 1988, 1994, 2000; Langford, Schoenfeld, & Izzo, 2002; Morgan, 1997; Onwuegbuzie et al., 2009).

Krueger (1994) and Morgan (1997) suggest that three to six different focus groups sessions are adequate for reaching data saturation[19] and/or theoretical saturation.[20]

The focus group participants were all undergraduate students between the ages of 18-24 who were enrolled in the Psychology program at the University of Ottawa. The rationale for this targeted sample was twofold. The first consideration was instrumental in nature. It focused on how best to recruit participants. Fortunately, the University of Ottawa has a program in place to assist in dealing with this matter. All the participants were recruited through the University of Ottawa's Integrated System of Participation in Research (ISPR) collaboration.[21] This initiative serves to unite university researchers and students enrolled in the university's Psychology and other partner programs (e.g., Communication) to facilitate the recruitment of research participants. As per the ISPR guidelines, individuals who participated in my study each gained two points (or 2%) towards one of their final grades. The second consideration was a matter of personal interest, as one of my main research objectives was to investigate the level of algorithmic literacy present among a population which I assumed would be (or should be) among the most familiar with algorithms, hence my decision to target undergraduate students.

In designing and conducting the focus group sessions, I was guided by the 9-step approach set out by Stewart et al. (2007, pp.37-50).

1. Formulation of research question
2. Identification of sampling frame
3. Identification of moderators
4. Generation and pretesting of interview guide
5. Recruiting the sample

[19] Data saturation occurs when the information collected across the different interview groups is recurring; in which case collecting more data appears to have no added value to the ongoing research project. See, Onwuegbuzie et al., (2009).

[20] Theoretical saturation is met when the researcher deems that their premise or theory is adequately developed and hence no additional data is required. See, Onwuegbuzie et al., (2009).

[21] See, https://socialsciences.uottawa.ca/psychology/research/participate-research/ispr-student-pool

6. Conducting the group
7. Analysis and interpretation of data
8. Writing the report
9. Decision-making and action

The first three of the above steps were addressed via Phase 1 of my project. The last step – decision-making and action – was not applicable because my project had no objective of advancing a specific action or decision. Hence, I opted to streamline Stewart et al.'s approach into the following three steps:

1. Focus Group research design,
2. Conducting and reporting the focus group, and,
3. Analysis and interpretation of data.

To ensure the appropriateness and quality of the questions used in the discussion protocol, two pilot sessions were conducted prior to conducting the actual focus group sessions. The first was very informal and involved probing draft questions with two family members to verify whether the questions were clearly phrased and if my family members were interpreting them in the manner I intended. The feedback from my relatives who — like the anticipated participants — did not have in-depth knowledge about algorithms, made clear to me that my initial draft questions needed to be rephrased in a more straightforward manner so as to ensure the discussions they prompted aligned with my central research question.

The second pilot session involved five close friends and was somewhat more formal insofar as it replicated the full process of conducting a focus group meeting via Zoom. Here, once again, I was hoping to ascertain the efficacy of my draft questions while also seeking to practice moderating and leading focus group sessions. Through this exercise, I was able to ascertain that the revised questions in my discussion protocol elicited the types of responses I was looking for and to confirm that the time allotted for each question allowed everyone to fully engage.

Students registered to participate in my project via the ISPR portal. Four timeslots were opened for inscriptions and spots were allocated on a first come, first serve basis. Due to the failure of five students to attend their scheduled meeting,[22] the final total sample size was 19, of which 11 identified as female and eight as male. The actual focus group meetings were held over a 2 week-period spanning from February 9th to 17th 2022. When signing up to participate in my project, students had to choose one of four timeslots, each of which was associated with one of four groups, three of which – G1, G2, G4 – ultimately were comprised of 5 participants and one of which was made up of four participants (i.e., G3). In keeping with the public health guidelines in place at the period during which the meetings occurred, each of the four focus group discussions took place virtually via the Zoom videoconference platform. The use of Zoom had the added benefit for facilitating the video and audio recording of the meetings.

As noted above, the focus group discussions were structured around six predefined open-ended questions that were formulated in accord with the five themes that emerged from the systematic review of the literature as being central to the concept of algorithmic literacy (i.e., algorithmic functionality, power and governance, personalization, ethics, and privacy). The sixth question connected to each of the 5 themes. The decision to structure the focus group sessions around six opened-ended questions was premised on my interest in collecting the participants' experiences, ideas, and perceptions relating to algorithmic literacy as opposed to collecting data, facts, or statistics about this topic (Oppenheim, 1992). As such, the questions posed were aimed at generating discussions among the participants about their knowledge and perceptions of

[22] As part of the ISPR operational protocols, after each focus group session, I was required to log attendance at the ISPR portal. Students who had registered to participate but who failed to attend without having advised me ahead of time were logged as 'unexcused no-show,' which meant they did not receive the 2% credit. Those who advised me in advance of their inability to attend were logged as 'excused no-show' and received the 2% credit despite their absence.

algorithms (see, Box 4.1). In other words, the use of opened-ended questions enabled my participants to “express their own ideas spontaneously in their own words” (Oppenheim, 1992, p.70).

Box 4.1: Focus Group Interview Guide

Q1. Think about the social media platforms you use on a daily basis. What is responsible for selecting the types of content (posts, ads, videos, etc.,) you see?

Q2. What are algorithms?

a. When you hear the word "algorithm", what comes to mind?

b. What are algorithms used for?

c. Where do we find algorithms? (or in which context are they used)?

Q3. Algorithms are frequently used for personalization purposes (i.e., to mediate & tailor content and experiences for each user). What are your thoughts on personalization?

a. Is data privacy something you think about when you navigate online? Why?

b. Do you think data privacy and algorithmic personalization are related concepts? Please explain.

Q4. Do algorithms exert power over your life? How so?

Q5. AI algorithms are increasingly used in various decision-making activities. For example, AI algorithms are being used in the U.K. and in the United States to help make decisions about benefit claims and welfare eligibility. Policing algorithms are also used in several countries (including Canada) to identify potential delinquency hotspots. Algorithms are even used in healthcare to predict patients who have a higher risk of developing illnesses such as breast cancer and heart disease. This has ignited debates about algorithmic decision-making. Are algorithmically rendered decisions more impartial than those rendered by humans? Why? Why not?

a. What is algorithmic bias?

b. Have you ever encountered algorithmic bias?

Q6. Should governments intervene to regulate and minimize the power algorithms have over digital spaces? Why? Why not?

Each focus group session largely followed the funnel approach to discussing the issues at hand. This involved opening the discussions with a broad question aimed at easing the participants into addressing more narrow and specific probes as the sessions progressed. To this end, the first question indirectly introduced the issue of algorithmic personalization without specifically revealing the fundamental issues of concern (i.e., algorithms). The second touched upon the theme of algorithmic functionality. The third delved into connections between algorithmic personalization and data privacy. The fourth question sought to encourage participants to reflect on issues of algorithmic power and governance. The fifth was targeted towards issues of algorithm ethics. The final question tied the agenda together by introducing a conversation in which participants were invited to provide their own opinions about an issue that touched upon matters of algorithmic functionality, personalization, data privacy, power and governance, and ethics.

4.2 <u>Analyzing the contents of the focus group discussions</u>

The recordings of each meeting were transcribed by me.[23] When transcribing these discussions, I assigned a unique code to each participant in order to protect their privacy and ensure their anonymity. Each participant was coded with 'FG' followed by a number representing the focus group in which they participated, and a 'P' followed by a number representing the randomly assigned order in which participants were asked to introduce themselves during the sessions. For example, the code FG1P3 represents a focus group participant from Group 1 who was the third person to be called upon to introduce themselves at the beginning of the session.

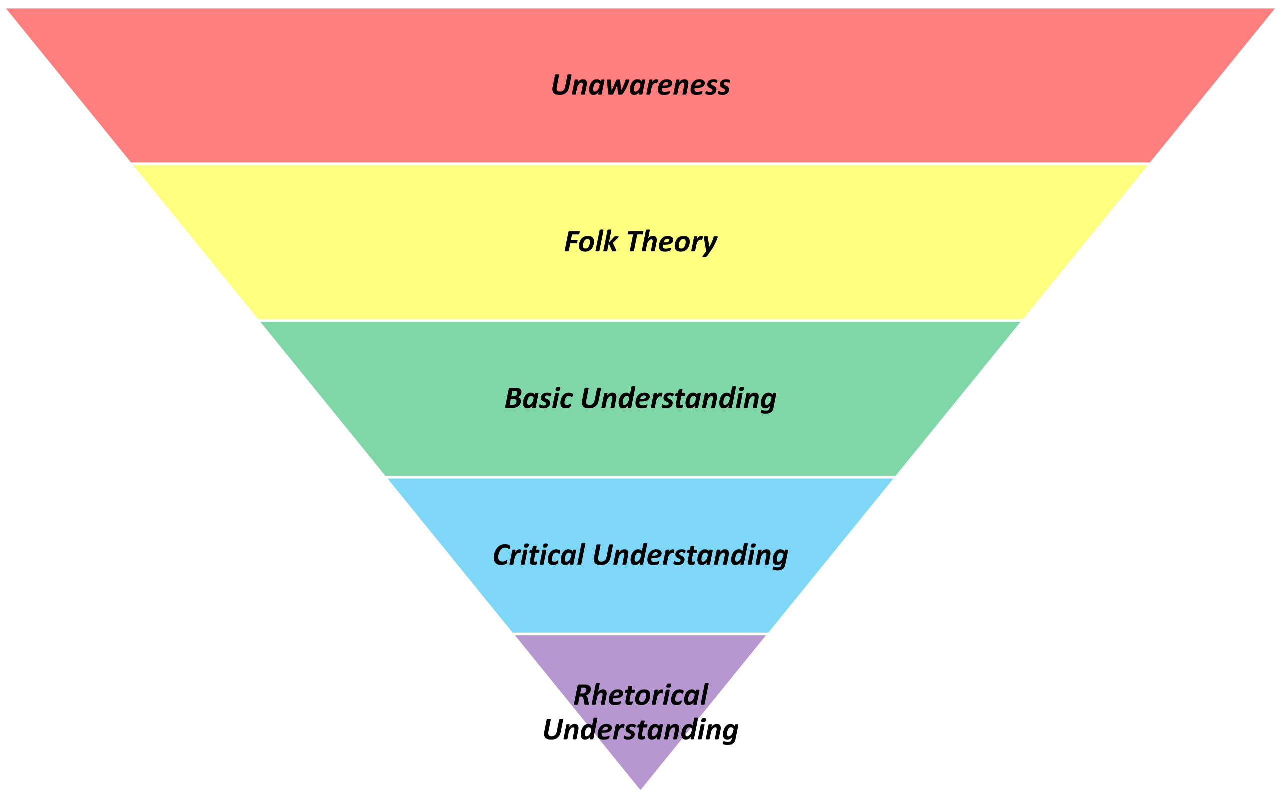
The analysis of the transcripts was divided into 3 steps. I began by breaking down and organizing each participants' responses to the focus group questions in accord with five categories of algorithmic literacy set out by Devito et al., (2017; 2018), Keoning (2020), and Selber (2004) (see Figure 4.1). Then, I sorted and regrouped the excepts by theme (algorithmic personalization, functionality, privacy, power & governance, and ethics) before finally tallying the number of occurrences recorded for each level of algorithmic literacy under all 5 themes.

The first level of understanding is 'unaware.' This category refers to explicit expressions of ignorance, unfamiliarity, and/or confusion about the topic being addressed. For example, in

[23] The transcripts were supplemented by some additional observational data captured during the meetings that communicated a participant's response or position regarding a certain topic or issue (e.g., nodding, shrugging, and other non-verbal cues).

response to the question about whether algorithms exert power beyond social media, FG2P5 stated: "I don't know, I wouldn't know. I mean, I don't think anybody really knows either." FG2P3 likewise stated they did not "know anything about algorithm bias" when asked about their views regarding the impartiality of algorithmic decision making.

Figure 4.1: Levels of Algorithmic Literacy



The second level of awareness, folk theory, refers to the intuitive and informal theories developed internally by individuals to understand and explain the possible outcomes, effects and/or consequences associated with technological systems (DeVito et al., 2017; 2018). Folk theories are often oversimplified and largely inaccurate. They tend to be based on personal interpretations and experimental information rather than verified evidence (Eslami et al., 2015 & 2016). Within the context of this thesis, folk theories are perhaps best understood as casual, speculative interpretations or assumptions made about what algorithms do. For example, when asked to define what algorithmic bias is, FG3P2 explained that they believed it "is like what [type of content] you're exposed to and that [exposure] would kind of influence your bias." This response is illustrative of someone who is attempting to make sense of algorithmic bias by reflecting on their lived experience and their experimental knowledge bases. It suggests a limited understanding of the ways in which algorithms can entrench, reproduce, and prompt biases beyond the realm of social media.

Basic understanding is the third category of algorithmic literacy. Within the context of this thesis, it is characterized by the participants' acknowledgement of the rudimentary concepts associated with algorithms and/or demonstration of basic knowledge of a particular algorithmic aspect or feature. Put simply, a basic understanding of algorithmic functionality entails awareness of what algorithms do, how they work (very broadly), and/or, where algorithms are deployed. For example, when asked about where algorithms are found, FG1P3 responded:

> you often feel the algorithm when it comes to ads. I find that algorithms are used to kind of tailor ads to hopefully appeal to the consumers interests and hope that they will click on the ad.

This response demonstrates knowledge of the use of algorithmic applications for advertising purposes online.

Whereas a basic level of algorithmic literacy involves understanding 'how,' in some capacity, algorithms function, the fourth level of understanding—critical understanding—involves also considering the 'why' (Koening, 2020). I add to this definition the capacity to integrate some of the algorithmic themes together and/or demonstrating a level of understanding about how one theme might relate to another. For example, participants with this level of understanding might consider the potential impacts, inequalities, consequences, and opportunities algorithms spawn for people, cultures, societies, processes, and institutions. When asked to define what algorithmic bias is, for instance, FG1P2 explained that, in some cases, algorithms pull their information from specific data sources and therefore, are “learning from a world that already has biases in it and by doing so it's [the algorithm] going to start to obtain those as well.” This response denotes an understanding of what algorithmic bias is, how it can occur, and the potential consequences this has on people and processes.

Rhetorical understanding constitutes the highest level of algorithmic literacy. It involves individuals being cognizant of the interconnectedness of human-algorithm interactions (Selber, 2004; Koening, 2020). A rhetorically aware user is able to verbalize how algorithms influence their actions, how their actions influence algorithms, and how this relationship influences society writ large. For example, when asked about the power algorithms exert over peoples’ lives, FG1P1 explained:

> I think they [algorithms] indirectly have power over you because at the same time that they do, you are influenced by them, the algorithm is also influenced by you. So it’s like a reciprocal relationship but like it does indirectly have power over what you see and what you'll think in the future but you can also refer sudden change to what the algorithm will show you.

The above comment demonstrate that this participant understands the basic functioning of algorithms and that they can reflect on this relationship beyond simple observation.

Once I finished coding the focus group transcripts, I organized the coded text by subject matter and literacy level. More specifically, I grouped the coded portions of text according to the overarching themes discussed (i.e., algorithmic personalization, functionality, privacy, power & governance, and ethics). Once grouped, the coded portions of text were categorized according to their corresponding level of algorithmic literacy. This exercise made it possible to discern the total number of times each theme was discussed during each session and, more importantly, to tally the total number of responses classified under each level of algorithmic literacy for each theme.

Since my interest was principally aimed at assessing the level of algorithmic literacy present among my sample, I chose to tally the responses on a group level. This meant that an individual could speak more than once on the same given topic without this impacting my census. The key component in this instance was assessing the level of algorithmic literacy exhibited to each response. This enabled me to ascertain the frequency at which each level of algorithmic literacy emerged during discussions which, in turn enabled this allowed me to identify the level that was predominant across all the responses collected.

Once I completed this exercise for all 5 themes, I replicated the process at the individual level by tallying every response provided by each participant. This enabled me to calculate a measure of average algorithmic literacy level for each participant.

4.2.1 Algorithmic Personalization

Questions 1 and 3 of the discussion protocol addressed the theme of algorithmic personalization. Question 1 invited the participants to elaborate on what they thought is responsible for selecting the type of content (such as posts, pictures, ads, links, etc.) they see when navigating online. It sought to identify whether participants were aware that algorithms are responsible for personalizing the content they see on social media platforms. Question 3, on the other hand, sought to identify the knowledge participants had regarding what algorithmic personalization is, what it is used for, where it occurs, and the effects and consequences associated with this process. When discussing matters of algorithmic personalization, the responses from participants in Groups 1, 3, and 4 predominantly fell into the category of folk theory. Participants from Group 2 recorded more answers demonstrating basic understanding (see Table 4.1). Overall, however, the answers documented across all four groups denoted many similarities.

Table 4.1. Classification and frequency of perspectives regarding algorithmic personalization

	Group 1	Group 2	Group 3	Group 4	Total
Unawareness	0	1	4	4	**9**
Folk Theory	9	4	6	10	**28**
Basic Understanding	7	6	5	9	**27**
Critical Understanding	2	0	1	0	**3**
Rhetorical Understanding	0	0	0	0	**0**
Total	**18**	**11**	**16**	**23**	***67***

A common concept that participants brought up when asked about what is responsible for the content selection on their social media newsfeeds was hashtags or tags. Four participants across the four groups (FG1P2, FG1P4, FG3P & FG3P3) mentioned hashtags or tags when asked about what they thought was responsible for selecting the content one sees online. For example, FG3P1 stated:

> When I think of a social media platform like TikTok for example, I would think that it would revolve around hashtags, and I would assume the content I consume has specific like hashtags that are known. For example, it could be sports or something, and the more [I watch this type of content, the more] they would pump sport content to me.

This response is illustrative of someone who is attempting to make sense of algorithmic personalization by associating the process to a more familiar concept (i.e., hashtags). It suggests the participant has a limited understanding of the ways in which previous online activity and preferences impact the content they see on social media. Similar responses gathered across the four groups were categorized as demonstrating a folk theory level of algorithmic literacy (n=28). Another recurring concept brought forth during discussions was cookies.[24] Eight participants from across the four groups (FG1P2, FG1P5, FG2P2, FG2P4, FG3P2, FG3P3, FG4P2, FG4P4)

[24] The term "cookies" refers to the means through which web browsers store data from websites accessed for online shopping, researching, and entertainment (including social media) to provide a personalized browsing experience notably by filtering and tailoring ads. See, Martin (2018).

expressed the view that cookies are responsible for selecting the type of content (such as ads) that appear on social media platforms. Although cookies are used to personalize online browsing experiences, these participants frequently conflated cookies and algorithms using these terms interchangeably. This suggests that familiarity with the idea of online personalization among these individuals was counterbalanced with limited knowledge and understanding of the role algorithms play in personalizing content.

While folk theory understandings prevailed overall when discussing algorithmic personalization, responses testifying to the presence of a basic level of understanding also were evident across the four groups (n=27). Most of the participants (n=14) acknowledged that their previous online activity and content interactions conditioned the type of content they received. The view expressed by FG1P2 is reflective of what was articulated by several participants regarding this matter:

> I would say, like, if we're talking about what I think is the reason behind the content that I get, it's mostly based off of my interactions with posts or, like, content and videos – I know that with certain platforms, like, with Tiktok for example, if you watch a video passed a certain point it registers that you actually enjoyed it.

Another demonstration of a basic level of algorithmic literacy was exhibited by FG3P2 who explained that:

> the algorithm is tailored towards what you like, and that can be dangerous because it can be addicting in a sense because since it's tailored to what you like. That is, what you would go more towards as opposed to other sources that would give more of, like, an overview or neutral […] non-biased opinion on something.

Here, the participant's comments were in reference to how algorithmic personalization can contribute to people re-affirming their beliefs through their information consumption habits on social media. Their statements demonstrate that they understand, to a certain extent, what algorithmic personalization is and what it does, along with some of the latent challenges to which this practice gives rise.

Three participants – FG1P2, FG1P1, FG3P4 – provided responses to the algorithmic personalization question that were illustrative of a critical understanding level of algorithmic literacy. For example, FG1P2 explained how algorithmic personalization on social media platforms can ultimately function to reinforce political beliefs by presenting and prioritizing content that subscribes to specific dogmas, thereby reaffirming, as opposed to challenging, people's existing beliefs.[25] In this instance, the participant's reflection suggests they understand what algorithmic personalization consists of, and demonstrates an awareness of how this practice has been linked to impacts and effects beyond the realm of social media.

Overall, 20 of the 67 responses gathered in relation to algorithmic personalization explicitly referenced examples of things the participants, or the people close to them, have noticed or experienced when navigating online. This suggests the participants construct their knowledge of algorithmic personalization foremost on the basis of their own lived experiences.

4.2.2 Algorithmic Functionality

Question 2 dealt with algorithmic functionality. It sought to investigate the participants' knowledge regarding what algorithms are, what they are used for, and where they are found. When discussing this matter, the members of Groups 1 and 2 predominantly put forward statements and observations suggesting they possessed a level of basic understanding whereas those advanced by members of Groups 3 and 4 tended more toward folk theory-based responses. Most study

[25] This observation echoes the notion of 'echo chambers' and 'filter bubbles.' The former refers to the highly personalized communication environments that result from social media users' ability to follow like-minded people (Lazer et al., 2017; Rhodes, 2022). The latter refers to algorithmically powered filter bubbles that result from algorithms prioritizing agreeable content to maximize users' time spent on the platform (Kitchens, Johnson, & Gray, 2020; Rhodes, 2022). The incidence and impact of both phenomena has been disputed (see, for example, Dubois & Blank (2018)) and continues to be a subject of research.

participants (N=12) were unable to formulate concrete and accurate responses concerning what algorithms are and struggled to define algorithms. The discussion among members of Group 4 generated nine responses that fell into the unawareness category (see Table 4.2). Indeed, Group 4 was the only group in which this category of responses was evident for this topic. Two participants indicated they did not know what algorithms are. FG1P1 defined algorithms as:

> any sort of thing that could make a link between two topics, or a person and a topic. Any sort of computation [that can] bring two things together without needing someone to manually input big ideas or make thoughts or model data or anything like that.

Likewise, FG2P5 advanced:

> I think an algorithm is… I'm pretty sure it's a pattern. I haven't researched it too much, but I think it's a pattern.

Table 4.2. Classification and frequency of perspectives regarding algorithmic functionality

	Group 1	Group 2	Group 3	Group 4	Total
Unawareness	0	0	0	9	**9**
Folk Theory	7	5	7	9	**26**
Basic Understanding	8	7	6	6	**27**
Critical Understanding	4	0	0	0	**4**
Rhetorical Understanding	0	0	0	0	**0**
Total	**19**	**13**	**15**	**23**	***67***

Across the four groups, folk theory-based interpretations of algorithmic functionality were the most frequently observed category of responses (n=26). The responses falling into this category shared the common trait of failing to clearly outline what algorithms are, with respondents offering vague interpretations seemingly fabricated on abstract understandings of algorithmic functionality.

A few participants (n=8) from across all four groups provided responses suggestive of a basic understanding, and two participants from Group 1 provided responses corresponding to a critical understanding of algorithms. FG1P4 indicated, "I do a little bit of programming so from my experience an algorithm is like a set of instructions that's set to complete a specific problem or issue and so a lot of it is doing it in the most efficient way possible." For their part, FG1P1 explained that algorithms are used

> to find a quick solution from point A to point B that is meant to be [done in] a fast way. A set of instructions to link an input to an output that, instead of finding the longest way over, [is done in] an efficient way.

Despite the general difficulty the participants had in attempting to define what algorithms are, their responses to queries about algorithmic applications (i.e., what algorithms are used for) and where algorithms are deployed suggested many possessed some awareness about algorithmic functionality. Aside from social media, the responses mentioned advertising (n=5), optimization (n=2), content mediation (n=3), recommendations (n=3), math/engineering (n=4), and search engines (n=3). It also merits noting that the majority of responses pertaining to functionality referred to algorithms within the context of online platforms and websites

The latter observation would, on the face of it, seem to support suggestions that those in the 18-24 years old demographic tend to acquire basic knowledge of algorithms through their engagements with online platforms and websites (see, for example, Eslami et al., 2015; Rader & Gray, 2015; & Cotter & Reisdorf, 2020). For example, FG2P2 explained:

> I think it's us [who decide what we see on our feeds] like what we search and what we watch. I watched the series *Arcade* not long ago and a whole bunch of advertisements for it started showing up on my Facebook feed. And, a while back, my sister watched slime videos on my YouTube account and my snapchat is just filled with satisfying videos of slime so now I can't get rid of it. So, I think it has a lot to do with what we ourselves look at and research or watch... it sounds like it's all sort of connected.

Another participant (FG4P5) provided noteworthy responses about algorithmic functionality by presenting ideas that were not brought up by any other participant. FG4P5's responses exemplify the types of narratives that can be tied to algorithms and their use. For instance, they explained how they believe algorithms are used to "change the perspective people

[have]" on various matters including self-image and political ideologies. Throughout the discussion, FG4P5 linked their own experiences on Instagram with algorithms and the body image issues they faced in their life. The participant suggested that algorithms were developed and implemented as marketing tools intended to modify people's behaviours and ideologies regarding beauty standards. FG4P5's reasoning demonstrates a certain level of understanding regarding the impact algorithms have on social media content mediation and about their use for targeted ads and marketing purposes. Nonetheless, this participant's reflections were predominantly, and almost exclusively, based on their own experiences and interpretations.

In another instance, FG4P5 confused the HTML source code of a webpage with algorithms and suggested that bus cards are also algorithms just like the machines used to validate the bus cards.[26] This example is illustrative of the types of reflections and assumptions individuals with lower levels of algorithmic literacy might make about algorithmic functionality insofar as they present confused narratives about algorithms and/or interpret technical features without understanding or knowing what they are or what they are used for. All in all, through their reflections, FG4P5 exemplified the folk theory level of algorithmic literacy.

In sum, these findings suggest most study participants possessed at least rudimentary knowledge and understandings of what algorithms are, what they are used for, and where they are deployed online. The propensity of the participants to articulate moderately informed responses in relation to what algorithms are used for and where they are implemented was contrasted by what appeared to be less informed understandings what algorithms are. Put simply, possessing limited knowledge – or, in some instances, the absence of knowledge – of what algorithms are, did not

[26] Although most card readers do use algorithms to validate identification numbers (i.e., the Luhn algorithm), the participant formulated her claim in a manner which implied that all technological tools *are* algorithms rather than *use* them. This suggested confusion on FG4P5's part regarding what algorithms really are and what they are used for.

preclude individuals from demonstrating some degree of understanding of how algorithmic applications function.

4.2.3 Algorithmic Privacy

Questions 3A and 3B focused on algorithmic privacy. They were posed to investigate the participants' views about the connections between algorithms and online privacy. The information presented in Table 4.3 shows that, of the five themes discussed in the focus groups, the participants were least knowledgeable about matters of algorithmic privacy. This theme recorded the lowest number of total responses (n=10) belonging to levels of understanding above that of folk theory.

Five participants (FG2P2, FG2P5, FG3P1, FG3P4, FG3P3) asserted that details regarding how their personal data is used by platforms is concealed and/or hard to access because it is in lengthy Terms and Conditions statements which, in turn, discourages them from seeking out information about the topic. Four others indicated that they did not feel concerned by issues of data privacy because they do not consider their data to be relevant or important. Ten participants pointed out that they surrender to data collection practices despite their underlying concerns because they view it as something inevitable that will occur regardless. They deemed online privacy to be non-existent or impossible. For example, FG4P3 explained

> I think it's [data collection] going to happen anyway and by the time we're even aware of it, it's probably already happened if you're on social media or the Internet. As a kid or a young teen, the data is already there; nothing goes away on the Internet it's always going to be there.

Participants also elaborated their commentary by implying that although their personal data is being collected by social media companies such as Facebook that track their activity and have access to their personal data, they are not ready to unsubscribe from these platforms. Such responses correspond to the folk theory level of understanding insofar as they illustrate interpretations derived from personal negotiations and observations about data privacy and algorithmic data collection processes while also exhibiting a level of cognizance and awareness of such practices.

Table 4.3. Classifications and frequency of perspectives regarding algorithmic privacy

	Group 1	Group 2	Group 3	Group 4	Total
Unawareness	0	5	2	0	**7**
Folk Theory	4	5	8	6	**24**
Basic Understanding	1	2	4	2	**8**
Critical Understanding	1	1	0	0	**2**
Rhetorical Understanding	0	0	0	0	**0**
Total	**6**	**13**	**14**	**8**	***41***

Several concepts and ideas recurred across the groups during the discussions about algorithmic privacy. The idea that mobile phones can eavesdrop on in-person conversations to optimize personalized ads on social media platforms was raised by five participants across three of the four groups. FG3P4's intervention is illustrative in this regard:

> I remember one time my friends were, like, testing it and we were just saying words out loud. I don't even know if my friend had her Instagram running or if it was shut, but the next day she got ads for some of the stuff that we were saying. So, it wasn't even something that she had searched up or that she had liked it was generally something we were just talking about and saying which was definitely creepy.

FG4P5 suggested that algorithms (or the company/entity behind the algorithm) are watching their users:

> who's to say that they're not actually watching us physically well – through a screen? Right? I remember I think about a year ago, there was this app that US military was actually spying on Muslims though.

Rooted in conspiracy theories and/or misinformation, this comment demonstrates FG4P5's mistrust and skepticism towards algorithms.

Four other participants (FG1P2, FG1P3, FG4P2, FG4P4) asserted that data privacy would only be relevant to them if they were public figures and/or if they assumed high-level positions in the public or private sector. This folk theory understanding appears to be founded in the idea that youths such as students, adolescents, and tweens are not targeted or impacted by data collection processes nor by matters of private data security because the data they generate is insignificant and/or holds little value. Such interventions further suggest that these participants have a limited understanding of the value their personal data holds, the ways in which their data can be used, and the effects data collection processes can instigate outside the realm of social media platforms.

The most common feature of the responses categorized as exhibiting a basic understanding of algorithmic privacy showed a propensity to link data collection processes with personalization processes and matters of privacy. Four respondents (FG1P2, FG1P5, FG2P4, FG2P2) conveyed an understanding of how their personal data was used for personalization purposes such as advertising and/or content mediation. FG1P5[27] demonstrated their understanding of how personalization occurs through personal data collection processes by stating:

> It's a little bit weird how everything [personal data] is being held on the internet and how it will be used. I think that we should worry about our own private data because you might just want to go on a website to see some stuff and chill out, but they [websites & social media companies] will collect your information and the next time they'll know what you want and it's not surprising anymore. It's like they know me well. So yeah, privacy is important.

Another notable element that was brought forth by four other participants (FG1P1, FG3P1, FG3P3, & FG32P4) was that algorithms can also draw from location data to personalize and cater content when navigating online. Three of these individuals made comments that were categorized as revealing basic understandings insofar as their statements revealed an awareness that matters of algorithmic privacy involve myriad features including, but not limited to, location services. The fourth individual, FG1P1, demonstrated a critical understanding when they stated that the ranking

[27] FG1P5's first language was not English therefore they struggled to clearly elaborate their thoughts. The grammar and syntax in the quote were reworked to ensure the message conveyed was clear for the reader.

of search engine results is impacted by factors such as location and provided an example to exemplify this occurrence. This response demonstrates a more advanced level of understanding than the others because it combines knowledge of algorithmic functionality, personalization, and privacy.

4.2.4 Algorithmic Power and Governance

The aim of the Question 4, which dealt with algorithmic power and governance, was to have the participants share their views about the way(s) in which algorithms exert power over their lives and how this power is manifest in daily life. The resulting discussions were dominated by responses corresponding to the folk theory (n=18) and basic understanding (n=13) levels of algorithmic literacy (see Table 4.4). Thirteen comments exhibited a basic understanding of algorithmic power and governance, and five demonstrated critical understandings. The only comment among the entire focus group sessions categorized as showing a rhetorical level of understanding was captured under this theme.

Table 4.4. Classifications and frequency of algorithmic power & governance mentions

	Group 1	Group 2	Group 3	Group 4	Total
Unawareness	0	1	0	2	**3**
Folk Theory	3	3	5	7	**18**
Basic Understanding	2	3	2	5	**13**
Critical Understanding	4	1	0	0	**5**
Rhetorical Understanding	1	0	0	0	**1**
Total	**10**	**8**	**7**	**14**	***40***

Nine participants explicitly stated that their answers were based on their own personal observations and experiences. This suggests that nearly half of the people included in my sample constructed their knowledge about algorithmic power and governance through the interactions they have previously had with algorithms and social media platforms. When asked whether they believed algorithms exert some sort of power over their personal lives, nine participants answered ‘yes’, four said ‘slightly’, four responded ‘not really’, and two did not specify.

Those who responded negatively supported their claims by stating that, despite the mediating role assumed by algorithms on social media, users ultimately have the power to steer and influence the content presented to them online. For example, FG3P1 explained:

> I wouldn't necessarily say that they exert some sort of power because ultimately, I could randomly decide to just stop enjoying what I used to enjoy, and it would just shift and keep shifting. So rather than it being a power, I feel like it's like an accessory to my life. It's there and I enjoy it and it is not imposing anything upon me.

The four participants (FG4P4, FG2P2, FG2P4, FG2P3) who provided a mitigated response (by responding ‘slightly’) acknowledged the existence of algorithmic power but stated that this power is limited to the realm of social media and content mediation. This points to an awareness of algorithmic power that does not appear to extend beyond one’s personal experience and which exhibits limited knowledge of the effects algorithms may engender outside the realm of social media.

Overall, nine participants articulated responses that exhibited a basic level of understanding and four provided answers reflecting a critical understanding. The most frequently documented notions in this regard were oriented around the idea that algorithms can and have affected society and individuals beyond the digital realm. For example, four participants (FG3P4, FG4P1, FG4P3, & FG4P4) supported their reflections by citing specific examples of instances where the circulation of false information and conspiracy theories online contributed to advancing problematic movements or ideologies. For example, FG3P4 mentioned the so-called freedom convoy that occupied the Ottawa city centre from January 22 to February 23, 2022, to illustrate how algorithms can have power and influence outside of social media:

> Look at the convoy as an example and the fact that it was a movement that started on Facebook, and it was mostly run through social media. People would create posts and post opinions about things that are anti-vax and then their algorithm would connect them to the convoy page because there's lots of anti-vaccine and anti-masks posts on there. […] So, I think that even though it's not directly affecting your beliefs, I think it can reaffirm them by allowing the algorithm to show you similar things so you only kind of get a one-sided story rather than a group of opinions.

For their part, FG4P1, FG4P3, & FG4P4 used the Covid-19 crisis and anti-vaccination campaigns as examples to support their claims. Such reflections attest to these students' knowledge of algorithmic power and governance insofar as their comments integrate a multitude of algorithmic themes and issues with concrete occurrences.

Lastly, one participant, FG1P1, provided an answer that corresponded to a rhetorical understanding of algorithmic power and governance when, in their comments, they acknowledged the reciprocal relationship existing between humans and algorithms while also recognizing the impacts that can result from this interaction.

4.2.5 Algorithm Ethics

Question 5, which sought to investigate algorithm ethics, invited the participants to share their reflections about a prevalent ethical challenge associated with the implementation of algorithms.[28] The question was designed to ignite conversations about the ethical challenges associated with the use and development of algorithms. In order to narrow the broad scope of this question, two sub-questions touching on the topic of algorithmic bias were incorporated into the discussion.

Of the five themes that were probed across the focus group sessions, algorithm ethics recorded the highest number of comments and observations falling into the critical understanding category (n=11). This said, and as was the case for the four other themes, here too, folk theory was

[28] Ethical considerations arising from algorithmic bias is a dominant theme in the evolving domain of what many loosely call 'algorithm studies.' See, for example Lloyd, 2019; Tsamados et al., 2020; Cotter & Reisdorf, 2020; Bakke, 2020; Hobbs, 2020; Koening, 2020.

the most frequently observed (n=30) level of algorithmic literacy (see Table 4.5).

Table 4.5. Classifications and frequency of algorithm ethics mentions

	Group 1	Group 2	Group 3	Group 4	Total
Unawareness	2	5	1	2	**10**
Folk Theory	7	4	9	9	**30**
Basic Understanding	5	11	6	3	**25**
Critical Understanding	6	4	1	0	**11**
Rhetorical Understanding	0	0	0	0	**0**
Total	**20**	**24**	**17**	**14**	*75*

Responses categorized as folk theory based exhibited little to no awareness of algorithmic bias and/or presented reflections that elaborated upon anecdotal information resulting from personal observations and experiences. In seven instances participants interpreted algorithmic personalization as being a form of algorithmic bias. These assertions were premised on the idea that algorithms present biased content (i.e., content that is 'biased' towards personal preferences) and imbed biases within individuals by presenting and prioritizing certain types of content. Despite containing a relevant element—that is, that algorithms can contribute to reinforcing biases within individuals by means of personalization—the propensity to speak of bias in this particular manner raises questions about whether these participants were aware of the ways in which algorithms can inherit, entrench, and reproduce other types of biases.

Responses falling into the basic understanding level (n=25) mainly consisted of somewhat vague explanations of algorithmic bias that nonetheless acknowledged some rudimentary notions associated with the theme of algorithm ethics. For example, FG2P2 described algorithmic bias as: "either bias in the equation and math that goes into it, like discounting information because it doesn't suit the need or the outcome for it, or it's bias in the creation of the algorithm like discounting gender or something like that." This answer exhibits a basic level of understanding insofar as it acknowledges key rudimentary elements associated with one facet of algorithmic bias such as embedded and encoded bias. For their part, responses categorized under the level of critical understanding exhibited richer analyses by also considering the latent consequences of algorithmic bias. FG2P5, for example, explained:

> When you make the pattern or the equation you kind of have to make it specifically for something and I guess you don't always know it, but that is bias. If it's one person making it, they might have like an opinion on what it is really or what they're trying to do and then the pattern or the code is obviously going to discriminate against anything else that does not fit in the category that it is looking for.

Here, the participant was able to verbalize, how bias is coded into algorithms and the consequences this can have on a larger scale. In addition, this individual supplemented their analysis by providing the following example "[…] I was just also thinking about the facial recognition thing, like if it's made specifically for one face or facial structure or colour of skin, then it's going to discriminate from anything that like goes away from that standard."

4.2.6 Overlapping Levels of Algorithmic Literacy

In some cases, participants exhibited overlapping levels of algorithmic literacy in a same given response. For example, FG1P2 explained how

> Algorithms can be found everywhere. The same thing applies, like, TiktTok, and Instagram all have that similar sort of same thing. I know 'cause at one point I was more involved in doing art on Instagram and I follow a lot of artists accounts and these artists were talking about how you took up changing the algorithm where is like putting a bunch of hashtags is really helpful but then like if you put too many hashtags it looks back and like it reduces your viewings and its reach so kind of like every app, every social media platform has that sort of thing and its tailored to the content they want.

Here, the participant indicates they are aware that algorithms are used on social media platforms (basic knowledge), before explaining how their art hobby on Instagram brought them to notice the fact that artists had to adapt their strategies when posting content on the platform to ensure they were attaining their desired exposure (folk theory level). Then, they expressed that every social media platform has their own unique algorithm(s) which are in constant evolution (Critical understanding). Similar instances during which a participants exhibited more than one level of algorithmic literacy in one response were recorded 64 times.

As previously mentioned, participants regularly substantiated their responses with anecdotes derived from their own experiences and/or those of their friends and relatives. This resulted in frequent instances where participants exhibited levels of literacy above that of folk theory (such as basic or critical understanding) which they supported with folk theories. As such, it was relatively common for an individual to exhibit different literacy levels all at once and/or when discussing a same theme. This supports the idea that the different literacy levels overlap with one another and are not reflective of definitive states of knowing versus unknowing. This observation is also consistent with the fundamental tenet of multiliteracies according to which individuals develop and foster a multitude of literacies with varying levels of understanding over their lifetime (Cope & Kalantzis, 2009).

Similarly, as demonstrated throughout this chapter, the focus groups participants showed varying levels of algorithmic literacy depending on the theme discussed. For example, FG2P4 provided responses that exhibited unawareness when discussing matters of algorithmic privacy and algorithm ethics however, some of the responses they provided on algorithmic functionality and algorithmic power & governance showed a level of critical understanding. Similar examples are applicable to all 19 participants, with no one participant exhibiting the same level of algorithmic literacy in each of their responses. This suggests that literacy levels can vary from one topic to another; an individual might be unaware of certain matters related to algorithmic privacy and algorithm ethics however this would not preclude them from demonstrating higher levels of literacy on other topics such as functionality and power & governance.

4.3 <u>What do the Findings Suggest?</u>

Folk theory was the most common level of awareness among the sampled population (see Table 4.6). Responses anchored in this level of algorithmic literacy were recorded 129 times across the four focus group sessions. The second most-common level of literacy was basic level understanding. Some 107 instances of this response type were recorded.

Table 4.6 Total Frequency of Responses by Literacy Level

Response Category	Frequency of Responses
Folk Theory	129
Basic Understanding	107
Unawareness	40
Critical Understanding	28
Rhetorical Understanding	1

At an individual level, nine participants predominantly provided folk theory responses (FG1P2, FG1P3, FG3P1, FG3P2, FG3P3, FG4P1, FG4P2, FG4P3, FG4P5), while 4 (FG2P2, FG2P4, FG2P5, FG3P4) mainly exhibited basic understandings, 3 (FG1P5, FG2P1, FG4P4) provided equal parts of folk theory and basic understandings, 2 (FG1P4, FG1P1) more commonly demonstrated critical understandings and one (FG2P3) participant more frequently presented complete awareness. The information presented in Tables 4.6 and 4.7 indicates that folk theory understanding is the most common type of awareness among the participants which, in turn, suggests a relatively low level of algorithmic literacy.

When looking at all the responses collected across each of the five themes that are central to the concept of algorithmic literacy (algorithmic personalization, functionality, privacy, power & governance, and ethics), the findings show that participants expressed their unawareness most often (n=10) when discussing matters of algorithm ethics. This said, the ethics theme also recorded the highest number of responses categorized under critical understanding (n=11) with a notable gap between the runner-up; algorithmic power & governance (n=5). The highest number of responses consistent with a basic understanding (n=29) was recorded for the theme of algorithmic functionality, followed by algorithmic personalization (n=27) and algorithm ethics (n=25). As for the folk theory level, all five themes recorded a relatively close number of corresponding responses: the highest being algorithm ethics (n=30) and the lowest being power and governance (n=18).

Table 4.7 Individual predominant Literacy Levels

Response Category	Number of Participants predominantly exhibiting this response level
Folk Theory	9
Basic Understanding	4
Basic Understanding + Folk Theory	2
Critical Understanding	2
Unawareness	1

Algorithm ethics generated the greatest number of interventions (n=76) whereas algorithmic power and governance (n=40) and algorithmic privacy (n=41) generated the least. This is notable because despite algorithmic ethics being a theme for which the participants frequently expressed their lack of awareness, they had plenty to say about the topic, most of which related to their own lived experiences and interpretations.

Findings also show that participants exhibited more basic knowledge when discussing the themes of algorithmic functionality (n=27), algorithmic personalization (n=27), and algorithm ethics (n=25) respectively. Contrastingly, algorithmic privacy tallied the smallest number of basic knowledge demonstrations (n=8). Such indications suggest that the participants seemingly were most knowledgeable about matters of algorithmic functionality and personalization (especially with regard to social media) and least knowledgeable about algorithmic privacy.

This observation forced me to reflect on the difference between algorithmic awareness and algorithmic literacy. Within the bulk of the academic literature I reviewed, or otherwise engaged with in conducting this study, the two terms were frequently used interchangeably. The findings of my empirical investigation led me to conclude that the conflation of these two terms is something that, at an analytical level, should be avoided. I contend that a parallel is to be made between algorithmic awareness and the proficiencies captured in the folk theory and basic understanding levels insofar as the latter categories testify to an individual's cognizance of algorithms without substantiating their ability to make sense of the information beyond simple meanings and interpretations. Understood in this light, algorithmic awareness refers to anecdotal and experiential knowledge about algorithms. An algorithmically aware individual, then would be defined as someone who is cognizant of the existence of algorithms and who possesses basic knowledge of one or more features of algorithms in a variety of different contexts.

With this in mind, I posit the that the notion of algorithmically literate individuals only be used to describe instances where deeper reflections and understandings about algorithms are showcased. This could be manifest, for example, in individuals situating basic knowledge bases in broader contexts and applications, and/or by formulating analyses that acknowledge the implications and consequences associated with the implementation of algorithms along with their relation to, and with, other algorithmic notions and themes.

Applying the analytical distinction I have set out above to the observations that emerged from the focus groups discussions, leads one to conclude that, overall, the participants in my sample demonstrated algorithmic awareness first and foremost, with some occasional demonstrations of algorithmic literacies.

4.4 Conclusion

The findings presented in this chapter revealed the presence of notable variations in the awareness/literacy levels of my participants with regards to the five themes that are central to the concept of algorithmic literacy. This suggests that algorithmic literacy might be best understood and assessed from a register that considers the multifaceted characteristics of the concept and thus, argues for the need to think in terms of algorithmic literacies (plural) as opposed to literacy (singular). Furthermore, my findings suggest that the participants seemingly acquired some (if not most) of their algorithmic knowledge through their own experiences with algorithms online. The discussion in the next chapter focuses on the implications of my findings for the understanding of algorithmic literacy.

Chapter 5: Discussion and Conclusion

The discussion set out in this chapter situates the findings that emerged from the two phases of my project within the broader context of contemporary algorithmic literacy research. The discussion is divided into five sections. In the first section, I revisit the two research questions that guided my project. The second section of this chapter provides an analysis of the two key contributions emerging from my thesis and propose a new approach to inform the study of algorithmic literacy. Then, I propose potential directions for future research in section 3 and establish my study limitations in section 4. Section 5 wraps up the thesis with a concluding thought.

5.1 Addressing the central research questions

This thesis set out to address the following research questions:

1. *From a socio-technical perspective, what are the key components of algorithmic literacy?*
2. *What is the level of algorithmic literacy present among a sample of undergraduate students enrolled at the University of Ottawa?*

The systematic review of algorithmic literacy research published over the last 25 years in the fields of media and literary studies found no 'one' commonly agreed upon definition of algorithmic literacy. The diverse definitions that were identified revolve around five themes that seemed to undergird the concept of algorithmic literacy: functionality, personalization, privacy, power and governance, and ethics. Each theme encompasses a variety of ways of approaching, understanding, and investigating algorithms. To this end, it may be plausibly argued that a defining feature of the algorithmic literacy is its multifaceted nature.

Armed with this insight, I designed the second phase of my project in a manner that allowed me to investigate the algorithmic literacy levels of a sample of undergraduate students by interrogating their opinions, thoughts, and views about algorithms in relation to these five themes.

In turn, the participants' levels of algorithmic literacy were categorised on the basis of: Unawareness, Folk Theory, Basic Understanding, Critical Understanding, and Rhetorical Understanding. The findings emerging from the focus group discussions suggest the participants were largely familiar with the rudimentary elements of algorithms. However, their understandings of these mathematical engines tended to be anchored foremost in the folk theory and basic level of interpretation insofar as their responses and talking points were mostly based on accounts of their lived experiences and/or that of other people in their lives. This observation resonates with those reported in other studies that have sought to investigate algorithmic literacy and/or algorithm awareness (Powers, 2017; Rader & Gray, 2015; and Devito et al., 2018). Echoing the findings of Klawitter & Hargittai (2018), the observations from my focus group discussions also suggest that even among frequent and highly motivated users, only a select few possess advanced algorithmic skills.

My observations from these sessions also appear to align in some ways with those of Koening (2020) who found that among a sample of 20 undergraduate students, almost all participants showed some basic awareness of algorithmic functionality with instances of critical awareness being less common. Where my findings diverge from those reported by Koening pertains to their having recorded a high number of responses showcasing advanced rhetorical reflections about algorithms in which the students were able to articulate analyses that incorporated basic algorithmic knowledge into broader issues, contexts, and conclusions (i.e., rhetorical level of awareness); something not observed in my sample. This said, it merits noting that Koening's data was collected from two online courses that spanned across a 5-week summer semester with students completing digital media diaries in which they were required to answer and reflect upon new prompts every week. By contrast, participants in my study had little-to-no time to reflect in any in-depth manner about the questions they were asked.

In their investigation of the Facebook newsfeed algorithm Elsami et al (2015) found that some two-thirds of their sampled population (some 40 individuals of various occupations ranging in age from 18 to 64) were unaware of the algorithm's existence. By contrast, all the students included in my study were aware that algorithms are used on social media platforms (such as Facebook) and when asked to define what algorithms are, only two of the 19 participants indicated that they did not know what algorithms are despite knowing of their existence.

The findings from my study also resonate with those of Powers (2017) who examined how aware American college students were of news personalization, along with the actions and criteria that impact news selection and prioritization. Most participants in the latter study demonstrated awareness that their interactions with online platforms, their search and click histories, along their online social endorsements and those of others in their social networks condition the selection and prioritization of news items to which they exposed in Facebook, Google, and other online news sources. Likewise, most of the participants in my study acknowledged that their previous online activity and content interactions conditioned the type of content they received.

Given that higher levels of algorithmic literacy have been linked to factors such as occupation, education, and familiarity with/ use of online platforms (see Rader & Gray, 2015; Devito et al., 2018; Cotter & Reisdorf, 2020), I set out on this project believing it was plausible to assume that those in a younger age demographic would have more awareness of algorithms than their older counterparts given the extent to which the use of social media platforms has become integrated into young peoples' day-to-day lives. Moreover, in the intervening years between Elsami & al.'s (2015) and mine, algorithms have garnered tremendous positive and negative media coverage[29] which, presumably, has contributed to increasing the public's familiarity with, at least, the term 'algorithm.' The observations drawn from my focus group discussions calls into question the veracity of my initial hypothesis. Although my sample obviously is too small to permit the drawing of any generalizations, I cannot help but wonder if my observations about this matter may be illustrative of a more widespread lack of awareness about algorithms among young adults in Canada and elsewhere.

Perhaps most importantly, the findings and observations emerging from the two phases of my project point toward a major shortcoming with my project. Namely, that the central research question guiding my study was fundamentally flawed. As phrased, my research question implies that 'algorithmic literacy' is to be conceived of as a state of knowing versus unknowing. Yet, my findings and observations clearly demonstration that algorithmic literacy is comprised of a multitude different type of literacies. Therefore, a viable empirically grounded response to cannot be provided to the question *What is the level of algorithmic literacy present among a sample of undergraduate students enrolled at the University of Ottawa?* because it turns out this question is a non sequitur. Put simply, it cannot be answered because it is rooted in an error of reasoning – i.e., contrary to my starting premise, algorithmic literacy is not a siloed phenomenon; it is multifaceted. As the findings from my research suggest, there are different types of knowledge that constitute the various facets of algorithmic literacy and, as such, that levels of algorithmic literacy vary across and within different thematic categories of algorithmic considerations.

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[29] See, for example, Cambridge Analytica scandal: https://www.nytimes.com/2018/04/04/us/politics/cambridge-analytica-scandal-fallout.html ; Algorithms to predict crime: https://www.bloomberg.com/news/articles/2022-06-30/new-algorithm-can-predict-crime-in-us-cities-a-week-before-it-happens ; The Facebook files https://www.wsj.com/articles/the-facebook-files-11631713039 & https://www.technologyreview.com/2021/10/05/1036519/facebook-whistleblower-frances-haugen-algorithms/ ; Discriminatory hiring algorithms https://www.wired.com/story/ai-hiring-bias-doj-eecc-guidance/ ; and Instagram and small businesses https://www.nytimes.com/2022/03/22/dining/instagram-algorithm-reels.html

5.2 <u>Key contributions</u>

There are two principal contributions advanced by my study, one of which holds pragmatic implications for algorithmic literacy research and one whose implications are theory centred.

5.2.1 Implication of algorithmic awareness without algorithmic literacies

At a pragmatic level, there is an ever-growing chorus of concerns about the need to increase critical thinking and general awareness about the role algorithms, and algorithmic processes, play in everyday life (see Bucher, 2018; O'Neil, 2016; Noble, 2018; Eubanks, 2018; Diakopoulos, 2019; Finn, 2017; Hasselberger, 2019; and Oldridge, 2017). As previously noted, the sample in my study was too small to allow for generalizations. However, it certainly seems plausible that the finding of low to basic levels of algorithmic literacies among the participants may be illustrative of their being vulnerable in the face of such algorithmically instigated issues as discrimination, inequality, data-surveillance, spam, manipulation (through the use of targeted ads or false articles), and so forth. Verifying this hypothesis would, of course, be contingent upon further empirical investigation.

One facet of these concerns that has recently garnered much attention pertains to algorithms and algorithmic systems hindering human autonomy by shaping users' choices and by limiting their ability to understand important information and/or make appropriate decisions (Andrejevic, 2019; Tsamados & al., 2020; Grafanaki, 2017; & Mittelstadt et al., 2016). Such concerns often are linked to, or echoe, Shoshana Zuboff's (2019, 2015) notion of Surveillance Capitalism which she defines as the emergent surveillance-based economic order resulting from the conversion of private data into fungible commodities on the economic market. Without adequate knowledge and understanding of algorithmic privacy and informational privacy, internet users are defenceless regarding the ways in which their personal data is being used, profited, and how this might affect their lives. Algorithmic privacy was one of themes for which the lowest level of algorithmic literacy was identified among my sample, with most participants struggling to fully grasp the ways in which their personal data can be, and is, used for commercial purposes, and how this can impact their lives beyond the realm of social media.

5.2.2 Algorithmic literacies

Perhaps the most notable finding to emerge from my study is the conclusion that, rather than approaching algorithmic literacy as though it is a unitary phenomenon, it is appropriate and useful to approach this concept in terms of diverse algorithmic literacies not least because people encounter myriad algorithms in myriad contexts every day.

Several parallels can be made between the notion of digital literacies and that of algorithmic literacies. The first similarity concerns the way in which knowledge is manifested. In their investigation of digital skills, van Deursen & van Dijk (2010) established that digital knowledge and skills involve sequential levels of understanding rather than definite states of knowing versus unknowing. My findings seemingly echo this assertion insofar as the participants in my study demonstrated that expressing unawareness during discussions did not mean they were completely unaware or unknowledgeable. Moreover, the exhibiting of low levels of algorithmic literacies when discussing a certain theme did not preclude individuals from showing higher literacy levels about other themes. For instance, the participants in my study demonstrated varying levels of algorithmic literacy simultaneously depending on the topics and themes being discussed. And, in some cases, individuals provided responses exhibiting varying levels of understanding when discussing a same subject matter! This observation offers a basis for positing that algorithmic literacy may be most effectively assessed, studied, and understood by recognising the multifaceted competencies and contexts of which it is comprised, similarly to the way digital literacies are approached today.

Building on this idea, I establish a second parallel by revisiting my early discussion regarding the expansion of the notion of digital literacy towards the pluralistic form of digital literacies. I suggest a possible overlap between the linguistic evolution of the concepts of algorithmic and digital literacy. Since the late 1990s, our understanding of the latter has evolved to encompass an ever-growing range of complementary literacies pertaining to new digital communication channels and features. Whereas in 1996 many were interested in fostering digital literacy, a quarter century later the term *du jure* is: digital literacies; an overarching term that regroups a multitude of contemporary literacies such as internet literacy, computer literacy, media literacy and algorithmic literacy (Bawden, 2001, 2008; van Dijk & van Deursen, 2014; Cope & Kalantzis, 2009; Dudeney, Hockly, & Pegrum, 2018). In more recent years, researchers and organizations have sought to incorporate and identify the essential elements that make up digital literacies in an effort to better incapsulate what the competence involves. For example, Belshaw (2012) identified and explored eight central elements of digital literacies. He suggested that digital literacies involve:

- understanding the various digital contexts an individual may experience (cultural)
- the mind habits developed from using various digital tools (cognitive),
- creating new content through remixing content from other sources (constructive),
- the intricacy of communicating in digital networked environments (communicative),
- understanding that digital environments allow for easier experimentation as opposed to physical environments (confident),
- the capacity to complete new tasks using new techniques (creative),
- observing, reflecting and/or questioning the power structures behind digital literacies and digital literacies contributors (critical)
- and the ability to use digital environments to selforganise into social movements (civic) (Belshaw, 2011; and Belshaw, 2012).

For their part, the Joint Informations Systems Committee (JISC) defined digital literacies as the "capabilities which fit someone for living, learning and working in a digital society" and identified seven essential elements of digital literacies which are: media literacy, communications and collaboration, career and identity management, ICT literacy, learning skills, digital scholarship, and information literacy (Joint Information Systems Committee, 2014).

On the basis of the findings emerging from my project and those reported in much of the literature reviewed for this thesis, there appears to be solid grounds for thinking foremost of algorithmic literac*ies* (plural) as opposed to algorithmic literacy (singular).

Separating algorithmic literacy into several sub-components might result in generating deeper understandings of the myriad facets of algorithmic literacy and might also allow researchers to identify with more certainty the types of algorithmic literacies that are best known and understood versus those that are not. Speaking of algorithmic literacies arguably allows for each sub-component to be defined more easily and with more precision instead of making researchers grapple with the complex, large, and overarching competence that is algorithmic literacy.

5.3 Directions for future research

My research project sought to investigate the level of algorithmic literacy present among a sample of undergraduate students enrolled at the university of Ottawa. The findings point to a number of possible areas warranting future research. The issues identified below are indicative of certain lines of inquiry that would, in my opinion, benefit from attaining increased scholarly attention:

1. *Algorithmic literacies among other demographics.* Finding rather low levels of algorithmic literacies among my sample has led me to question what one might find if similar research was conducted among seniors or children. To this end, future research could—and in my opinion should— investigate algorithmic literacies among individuals of various age

ranges and occupations in order to identify the levels of algorithmic literacy present among different populations and/or the general population all together. It would also be interesting to conduct similar research on a larger scale and compare findings between two populations and/or two generations as this could shed light on the factors that can contribute to fostering higher vs lower levels of algorithmic literacies.

2. *Fostering algorithmic literacies.* As previously established, the findings of my research suggest the presence of somewhat low levels of algorithmic literacies among my sampled population. I consider the issue of low algorithmic literacies to be an area of research that merits further attention. More specifically, increased research should be focused on identifying or developing approaches to increase algorithmic literacies so that individuals of all age ranges be better prepared to face, interact, and deal with algorithms and their repercussions. Research initiatives could seek to develop frameworks aimed at fostering higher levels of algorithmic literacies among various demographics such as children, students, working professionals, and seniors. Such research could involve conducting a systematic literature review to identify the educational tactics and methods that were/are most successfully used in practice for improving similar literacy proficiencies such as internet literacy for example. Drawing inspiration from what has been done and/or is being done to address issues such as digital divides, similar educational initiatives could be developed specifically for algorithmic literacies and tested among a sampled population. This could benefit the professional and educational domains by contributing to the advancement of knowledge regarding how to foster and/or improve algorithmic literacies in school and/or in the workplace.

3. *Algorithmic literacies beyond the Internet.* The participants in my study acquired much of their algorithmic knowledge through their online experiences and encounters. I believe it would be valuable to investigate the types of algorithms that are less commonly encountered and/or that are used for purposes other than that of social media. Such research could seek to assess algorithmic literacies present among a sampled population but with an exclusive focus on the types of algorithms used beyond the realm of social media and the internet for example, it could focus on algorithms that are used by government agencies for social services, public safety and/or for criminal justice. This research endeavour could adopt methods similar to those I used in my study to determine where individuals stand with regards to their knowledge of less common types of algorithms in order to identify the algorithmic aspects, applications and/or outputs that are more or less understood at large. The findings of this endeavour could help shed light on how algorithmic knowledge is constructed all while identifying with more certainty the types of algorithms that would benefit from additional scholarly attention in the optics of hopefully developing educational initiatives that would help address the potential knowledge gaps identified.

5.4 Study limitations

The results of my empirical investigation as well as the conclusions that can be drawn are constrained by a few limitations that must be acknowledged. First, the size of my sample limits the scope and generalizability of my findings. Seeing that my focus group research involved only 19 participants, my findings cannot be generalized across the whole target demographic. Considering that my research was completed as part of my master's thesis, the parameters of my study had to remain within manageable size. Nonetheless, it seems plausible that my results may be indicative of what one might find if similar research was conducted on a larger scale.

Furthermore, the results of my investigation might have been impacted by the fact that all the participants recruited in my study were enrolled in the psychology program at the University of Ottawa. It is plausible that the level of algorithmic literacy observed among my sample would have been different had I chosen to include students from various programs and departments (such as engineering or arts, for example).

Another limitation pertains to the format of the focus group discussions. Due to the Covid-19 pandemic, the sessions were conducted virtually via the video conferencing platform Zoom. I found that the virtual format hindered some of the natural flow of the discussions. At times, several participants would try to answer the same question all at once and would cut each other off which would cause the audio to glitch. It is likely that conducting live sessions would have made it easier for everyone to communicate their thoughts freely and perhaps would have allowed certain ideas to be explored more in depth. Second, I noticed that some participants would disengage during the discussions: some individuals looked at their phones or talked with a relative who was close-by. This led me to question whether I had everyone's full attention throughout the meetings. It is plausible that this might have had an impact on the depth and accuracy of the answers provided. As the researcher, I tried my best to keep everyone engaged by calling on those who spoke less often and by managing turns when I deemed it necessary to do so. It is also possible that the environment in which each student was made them feel less comfortable to speak their minds freely. The presence of family members or friends in the background might have led them to refrain from saying certain things by fear of being judged or ridiculed.

5.5 Final word

I became interested in studying algorithmic literacies three years ago in a graduate-level course taught by Professor Daniel J Paré focusing on algorithmic culture. I was baffled to see how little I knew about algorithms despite holding a bachelor's degree in communications, digital media and I became concerned that such important issues were not better known by the public. This reflection became the foundation of my Masters' thesis. From the start, I expected to find low levels of algorithmic literacy. I grounded this hypothesis in my own experience as well as the background research I conducted at the start of my dissertation. Although I cannot say I was surprised to find low levels of algorithmic literacies among my participants, I was happy to observe a progression between my findings and those of studies conducted a few years ago. Indeed, the broad findings of my research have contributed to highlighting the evolving dynamics of literacy practices by suggesting that algorithmic literacy competences have increased over the years (albeit at a slow pace). My findings also suggest that individuals acquire knowledge of algorithms through their repeated interactions with them. This observation brings me hope that algorithmic literacy proficiencies will continue to progress over the years to come.

Today, algorithms are central in all areas of social life. The algorithmic systems have direct consequences on human lives. As this thesis has shown, despite being increasingly subjected to algorithmic interactions and encounters, it seems as though individuals might still struggle with knowing and understanding algorithms and algorithmic systems. However, there is reason for hope; individuals are seemingly becoming more aware of algorithmic interventions online. Although there is arguably still a long way to go in terms of fostering critical and rhetorical reflections about algorithms, the results of my research lead me to believe that we are headed into the right direction.

Appendix 1: Full text screening inclusions (Level 2)

Level 2 – Full text screening inclusions (academic articles)

Refid	Bibliography	Nature of study	Methods & results	Technical Perspective	Algorithm knowledge
681	**Lloyd, Annemaree** (2019). Chasing Frankenstein's monster: information literacy in the black box society. *Journal of Documentation,* 75(6), 1475	Qualitative	Yes	No	Yes
682	**Koenig, Abby** (2020). The Algorithms Know Me and I Know Them: Using Student Journals to Uncover Algorithmic Literacy Awareness. *Computers & Composition*, 58	Qualitative	Yes	No	Yes
685	**Hobbs, Renee** (2020). Propaganda in an Age of Algorithmic Personalization: Expanding Literacy Research and Practice. *Reading Research Quarterly*, 55(3), 521	Qualitative	Yes	No	Yes
686	**Cotter, Kelly., & Reisdorf, Bianca. C.** (2020). Algorithmic Knowledge Gaps: A New Dimension of (Digital) Inequality. *International Journal of Communication*, 14, 745–765. Communication Source.	Qualitative	Yes	No	Yes
687	**Klawitter, Erin., & Hargittai, Esther.** (2018). "It's Like Learning a Whole Other Language": The Role of Algorithmic Skills in the Curation of Creative Goods. *International Journal of Communication* (19328036), 12, 3490–3510. Communication Source.	Qualitative	Yes	No	Yes
699	**Van Otterlo, Martijn** (2014). Automated experimentation in Walden 3.0: The next step in profiling, predicting, control and surveillance. *Surveillance & Society*, 12(2), 255	Qualitative	Yes	No	Yes
710	**Bakke, A.** (2020). Everyday Googling: Results of an Observational Study and Applications for Teaching Algorithmic Literacy. *Computers and Composition*, 57. Scopus.	Qualitative	Yes	No	Yes
715	**Dowdeswell, T.L., Goltz, N.** (2020). The clash of empires: regulating technological threats to civil society. *Information and Communications Technology Law*, 29(2), 194	Qualitative	Yes	No	Yes
723	**Cope, William, Kalantzis, Mary** (2009). "Multiliteracie": New Literacies, New Learning Pedagogies, 4(#issue#), 164	Qualitative	Yes	No	Yes

727	**Bucher, T.** (2018). Neither Black nor Box (Vol. 1). *Oxford University Press.*	Qualitative	Yes	No	Yes
728	**Hargittai, Eszter., Gruber, Jonathan., Djukaric, Teodora., Fuchs, Jaelle., Brombach, Lisa.** (2020). Black box measures? How to study people's algorithm skills. *Information, Communication & Society*, 23(5), 764	Qualitative	Yes	No	Yes
729	**Tsamados, A., Aggarwal, N., Cowls, J., Morley, J., Roberts, H., Taddeo, M., & Floridi, L.** (2020). The Ethics of Algorithms: Key Problems and Solutions. *SSRN Electronic Journal*.	Qualitative	Yes	No	Yes
730	**Mittelstadt, B. D., Allo, P., Taddeo, M., Wachter, S., & Floridi, L.** (2016). The ethics of algorithms: Mapping the debate. *Big Data & Society,* 3(2),	Qualitative	Yes	No	Yes
731	**DeVito, M. A., Gergle, D., & Birnholtz, J.** (2017). "Algorithms ruin everything": #RIPTwitter, Folk Theories, and Resistance to Algorithmic Change in Social Media. Proceedings of the 2017 CHI *Conference on Human Factors in Computing Systems*, 3163–3174.	Qualitative	Yes	No	Yes
732	**DeVito, M. A., Birnholtz, J., Hancock, J. T., French, M., & Liu, S.** (2018). How People Form Folk Theories of Social Media Feeds and What it Means for How We Study Self-Presentation. Proceedings of the 2018 CHI *Conference on Human Factors in Computing Systems*, 1–12.	Qualitative	Yes	No	Yes
733	**Kitchin, R.** (2017). Thinking critically about and researching algorithms. *Information, Communication & Society*, 20(1), 14–29.	Qualitative	Yes	No	Yes
734	**Beer, D.** (2017). The social power of algorithms. *Information, Communication & Society*, 20(1), 1–13.	Qualitative	Yes	No	Yes
735	**Willson, M.** (2017). Algorithms (and the) everyday. *Information, Communication & Society*, 20(1), 137–150.	Qualitative	Yes	No	Yes
736	**Eslami, M., Rickman, A., Vaccaro, K., Aleyasen, A., Vuong, A., Karahalios, K., Hamilton, K., & Sandvig, C.** (2015). "I always assumed that I wasn't really that close to [her]": Reasoning about Invisible Algorithms in News Feeds. Proceedings of the *33rd Annual ACM Conference on Human Factors in Computing Systems*, 153–162.	Qualitative	Yes	No	Yes
737	**Deursen, A. J. A. M. van, & van Dijk, J. A. G. M.** (2010). Measuring Internet Skills. *International Journal of Human-Computer Interaction*, 26(10), 891–916.	Qualitative	Yes	No	Yes

739	**D'Ignazio, C., & Bhargava, R.** (2015). Approaches to Building Big Data Literacy. 6.	Qualitative	Yes	No	Yes
740	**Reisdorf, B. C., & Blank, G.** (2021). Algorithmic Literacy and Platform Trust. In E. HARGITTAI, *Handbook of Digital Inequality*. Edward Elgar Publishing.	Qualitative	Yes	No	Yes
741	**Powers, E.** (2017) My News Feed is Filtered?, *Digital Journalism*, 5:10,	Qualitative	Yes	No	Yes
742	**Seaver, N. (2019)** Knowing Algorithms, chapter in *digitalSTS: A Field Guide for Science & Technology Studies*, edited by Janet Vertesi and David Ribes. Princeton: Princeton University Press, 412–422.	Qualitative	Yes	No	Yes

Appendix 2: Full text screening inclusions (non-academic documents)

Level 2 – Full text screening inclusions (non-academic documents)

Number:	**Reference**	**Included**
1	*Bigdataliteracy.net – CBDALN – Critical Big Data and Algorithmic Literacy Network.* (2021). https://www.bigdataliteracy.net/	yes
2	Fairness Toolkit. (2018, July 4). UnBias. https://unbias.wp.horizon.ac.uk/fairness-toolkit/	yes
3	Head, A. J., DeFrain, E., Fister, B., & MacMillan, M. (2019). Across the great divide: How today's college students engage with news. First Monday. https://doi.org/10.5210/fm.v24i8.10166	yes
4	Kids Code Jeunesse (KCJ) & the Canadian Commission for UNESCO (CCUNESCO), The Algorithm Literacy Project—Understanding algorithms. (2020). https://algorithmliteracy.org/	yes
5	Koenig, R. (2020, January 16). Report: Colleges Must Teach 'Algorithm Literacy' to Help Students Navigate Internet - EdSurge News. EdSurge. https://www.edsurge.com/news/2020-01-16-report-colleges-must-teach-algorithm-literacy-to-help-students-navigate-internet	yes
6	Rainie, L., & Anderson, J. (2017, February 8). Experts on the Pros and Cons of Algorithms. Pew Research Center: Internet, Science & Tech. https://www.pewresearch.org/internet/2017/02/08/code-dependent-pros-and-cons-of-the-algorithm-age/	yes
7	Simon Mueller & Julia Dhar. (2020, May 19). Algorithmic literacy – tomorrow's #1 skill everyone needs to learn. WeAreTechWomen - Supporting Women in Technology. https://wearetechwomen.com/algorithmic-literacy-tomorrows-1-skill-everyone-needs-to-learn/	yes

Appendix 3: Certificate of Ethics Approval

08/12/2021

Université d'Ottawa
Bureau d'éthique et d'intégrité de la recherche

University of Ottawa
Office of Research Ethics and Integrity

CERTIFICAT D'APPROBATION ÉTHIQUE I CERTIFICATE OF ETHICS APPROVAL

Numéro du dossier / Ethics File Number	S-11-21-6469
Titre du projet / Project Title	Encountering algorithms: Investigating the lived experiences of undergraduate students
Type de projet / Project Type	Thèse de maîtrise / Master's thesis
Statut du projet / Project Status	Approuvé / Approved
Date d'approbation (jj/mm/aaaa) / Approval Date (dd/mm/yyyy)	08/12/2021
Date d'expiration (jj/mm/aaaa) / Expiry Date (dd/mm/yyyy)	07/12/2022

Équipe de recherche / Research Team

Chercheur / Researcher	Affiliation	Role
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Appendix 4: Individual assessment of algorithmic literacy

Individual assessment of algorithmic literacy

	No awareness (red)	Folk theory (yellow)	Basic (green)	Critical (blue)	Rhetorical (purple)
FG1P1	0	5	5	7	1
FG1P2	1	9	8	6	0
FG1P3	1	6	3	0	0
FG1P4	0	4	4	5	0
FG1P5	0	4	4	0	0
FG2P1	1	6	6	1	0
FG2P2	2	6	12	1	0
FG2P3	7	2	4	0	0
FG2P4	2	3	5	2	0
FG2P5	4	5	7	4	0
FG3P1	0	8	6	1	0
FG3P2	2	10	4	0	0
FG3P3	3	9	4	0	0
FG3P4	2	8	11	1	0
FG4P1	3	8	7	0	0
FG4P2	4	9	2	0	0
FG4P3	2	9	8	0	0
FG4P4	3	7	7	0	0
FG4P5	3	11	0	0	0

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