

MASTER'S THESIS IN LIBRARY AND INFORMATION SCIENCE
FACULTY OF LIBRARIANSHIP, INFORMATION, EDUCATION AND IT

What do we talk about when we talk about
algorithmic literacy?
A scoping review

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English title: What do we talk about when we talk about algorithmic literacy? A scoping review

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Abstract:

Problem formulation, goal and objectives: Algorithms are ubiquitous in digital society, yet complex to understand and often hidden. Algorithmic literacy can be a useful concept when educating and empowering users. However, it is not uniformly defined or used, and the state of knowledge is unclear. The aim of this thesis is to examine algorithmic literacy as a concept, what other concepts are associated, and what empirical and theoretical knowledge exists on this topic.

Theory and method: Information literacy research serves as theoretical perspective, focusing on the role of evaluative and explorative approaches of research. The scoping review is chosen as method. Included are peer-reviewed journal articles, published in English from 2018 to 2022, from LISA, LISTA, ERIC ProQuest, and Scopus.

Empirical results: Algorithmic literacy is often placed in information, media, and/or digital literacies. Closely related terms are attitude, agency, trust, and transparency. Four themes were identified: the necessity of algorithmic literacy, algorithm awareness as the basis, teaching and learning, and studying algorithmic literacy. Demographic and socioeconomic factors play a role: lower age and higher education correlated with higher levels of algorithmic literacy. Algorithmic literacy is learned via personal experiences and formal education at all levels.

Conclusions: Algorithmic literacy research would benefit from a limited number of terms used, and clearly defined terminology. The relationship between closely related concepts needs to be examined further. Librarians and educators should develop and share interventions at regional or national levels. Various knowledge gaps have been identified that may serve as future research agenda.

Keywords: algorithmic literacy, information literacy, algorithms, media literacy, digital literacy, algorithm awareness

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1 Introduction

With the advances in computational power, machine learning, and technological innovations, algorithmic services have risen to the forefront. Algorithms now play a significant, yet often hidden, role in most people's daily digital lives: when using search engines (e.g. Swart, 2021), looking at social media feeds (e.g. Cotter & Reisdorf, 2020), and using streaming services (e.g. Kapsch, 2022) and a plethora of other digital services (e.g. Jiang & Vetter, 2020; Klawitter & Hargittai, 2018; Smythe et al., 2021).

The algorithms in these services sort and rank information, make decisions, and emphasise certain information at the expense of other. A simple definition of an algorithm is that it is a set of rules or instructions, which is followed by a computer program, and which solves some kind of problem (Dictionary.com, n.d.). However, users of these digital services are not always aware of the existence of algorithms. Those who are, often have little knowledge about them, although some users may have some ideas of their workings, and tactics about how to influence them (e.g. DeVito, 2021; Haider & Sundin, 2022a; Zarouali, Boerman, et al., 2021).

These services are often easy to use, and appear to offer objective information which people trust to base their decisions on. However, issues with these systems are significant, such as shifting the responsibility for disseminating information from publishers to anyone with access to a computer or smartphone (Limberg et al., 2012), enforcing bias (Noble, 2018), and potentially threatening democracy and leading to more inequality (O'Neil, 2016).

Studies have shown that information users might not be knowledgeable enough about algorithms in digital services to be able to make informed decisions about how to use them optimally and adequately to accomplish their personal or professional goals. This includes knowing how to assess information found through algorithmic systems critically (e.g. Cotter & Reisdorf, 2020; Kampa & Balzer, 2021; Klawitter & Hargittai, 2018). A clear role is cut out for improving algorithmic literacy as a way of educating and empowering information users in their daily interactions with algorithms, both in private and professional settings. Algorithmic literacy is often viewed as a further development of information literacy, media literacy, or digital literacies, including as computer literacy and data literacy (Bawden & Robinson, 2022; Cotter & Reisdorf, 2020; Dogruel et al., 2022; Garingan & Pickard, 2021).

1.1 Problem description, aims and objectives

As an emerging research topic in information literacy studies, a field riddled with diverse and inconsistent terminology (Bawden & Robinson, 2022), there is a limited amount of academic knowledge on algorithmic literacy. The topic is sometimes even studied 'by accident' through studies not specifically designed to investigate it (e.g. Cotter & Reisdorf, 2020; Klawitter & Hargittai, 2018). This leads to the problem statement: in the context of information literacy studies, algorithmic literacy is not discussed in a consistent and uniform way, and it is unclear what is known about this topic. The aim of this

thesis is thus to examine the current state of knowledge regarding algorithmic literacy, the terminology used, and its place in Library and Information Sciences research.

This leads to the following main research questions and sub questions:

1. What is known about the concept of algorithmic literacy?
 - How is it related to information literacy and other related literacies?
 - What terms are being used to describe algorithmic literacy and related topics?
2. How is algorithmic literacy being studied?
 - What do we know about algorithmic literacy from these studies?

In order to answer these questions a scoping review will be conducted, aiming to summarise and disseminate a broad scope of knowledge about algorithmic literacy, and identifying knowledge gaps and areas for future research. The study will include peer-reviewed academic articles published in the English language between 2018 and April 2022. The ambition is to make a contribution towards conceptualisation of algorithmic literacy, improving information literacy education and research in this aspect, and identifying topics for further research.

1.2 Relevance of scoping reviews in Library and Information Sciences

The scoping review is a highly relevant method for the research field of Library and Information Sciences, which may be due to its dynamic and interdisciplinary nature. Scoping reviews have been published in a wide range of topics, including information literacy instruction and assessment (Butler & Calcagno, 2020; Stapleton et al., 2020a; Urban, 2019), social media (Chugh et al., 2021; Kjellberg et al., 2016), knowledge representation (Neubauer et al., 2021), search (Damarell et al., 2019), the roles of librarians in systematic reviews (Spencer & Eldredge, 2018), and other work practices of librarians (Lorenzetti & Powelson, 2015; Nel, 2020).

Within the domain of medical librarianship the scoping review is especially common, which is not surprising given the method's roots in health sciences. Some of the topics covered are the role of the librarian in systematic reviews in health research (Spencer & Eldredge, 2018), librarians and health literacy (Klem et al., 2019), information literacy instruction for health sciences (Boruff & Harrison, 2018), and information behaviour of junior doctors (González-Teruel et al., 2021). Consequently, a scoping review of the concept of algorithmic literacy will have a solid place in a larger tradition.

1.3 Limitations

As with any study, there are limitations due to various choices and circumstances. A number of limitations can be mentioned with regard to the documents, query and terms, and databases chosen for this study. Some limitations can also be named given the fact that the work was done by a single researcher. These limitations are explained below.

Documents

In this review only journal articles are included, while conference papers and grey literature are left out. Any potentially relevant discussions in for example trade magazines are thus not taken into account. This choice was made due to time constraints, but in future research this literature could be included.

The decision to only include peer-reviewed articles also excludes potentially relevant academic articles that have not (yet) been peer-reviewed. This is the case for the review on algorithmic literacy by Oeldorf-Hirsch and Neubaum (2022), which has only been published in a preprint archive, and is therefore not included in the scoping review. By only including peer-reviewed articles the level of academic work is validated, something which would be much harder to do by oneself. If this scoping review would be extended in the future, any relevant articles that were not yet peer-reviewed in the period this study covers will be included at that later time – given that they have been peer-reviewed and published.

The decision to only review English-language articles omits all relevant articles that may have been published in other languages. This was a practical decision due to languages skills. Any future replication or extension of this review could include articles in any language the future researchers are confident users of. This is especially relevant for future research focusing on areas where languages other than English are used as academic language.

Query and terms

As described in Section 4.2, the query was relatively simple and required the presence of two terms: algorithms and literacy. The assumption was made that the term *algorithms* would appear in any relevant article. However, this does potentially leave out relevant documents which only use a broader, but closely related term, such as artificial intelligence or AI. Nonetheless, it is likely that most articles using these different terms would also use the term algorithm as they are so closely connected.

Similar limitations can be named for using only the term *literacy*. This potentially leaves out relevant documents that do not use this term but other terms that are tied to literacy, such as learning, teaching, knowledge or skills. However, since the concept of literacy was deemed crucial for the notion of algorithmic literacy, the decision was made to have it imperative to the query results.

Databases

While in many scoping reviews four to six databases are queried, Stapleton et al. (2020b) proposed that for scoping reviews in Library and Information Sciences research it might be more time efficient to query one specific and one broader scope database, in their case LISTA and Scopus. This was especially relevant if grey literature was also included in the review, and more time was needed to search in other sources than academic databases. Nonetheless, they explicitly warned this strategy might not be relevant for all topics in Library and Information Sciences and more evidence is needed to support their recommendations.

Given the relative novelty of algorithmic literacy, it was decided to use multiple specific databases so as to not miss anything relevant: both LISA and LISTA were included as subject databases for Library and Information Sciences, plus ERIC for education. As grey literature was not included in this review, the argument of needing time to search for this was not relevant. However, the advice to use only one broad scope database (Scopus), as opposed to two, was followed, since this would indeed save time inspecting results compared to including a second set of results of another broad scope database.

Consequently, it is likely that not all potentially relevant peer-reviewed journals are indexed by these databases, and some relevant articles may have been overlooked. However, it is expected that the topic is represented comprehensively enough for this review through the current choices of databases. This is explained further in section 4.2.

Single researcher

As I worked alone, there is a possibility of bias and errors when selecting and analysing the relevant articles. I have taken the utmost care to reduce this to the minimum by working systematically and iteratively, constantly checking and re-checking my work to increase consistency. Additionally, by adhering to the PRISMA-ScR guidelines for presenting a scoping review as much as possible (see Chapter 3) my work is transparent. However, working in a pair or team would benefit this type of research, as the processes and results could be decided upon by multiple people rather than one person, which may add to consistency and lessen bias and errors.

Working in a team would also provide the possibility of working with a more complex query resulting in a larger selection of relevant articles, as there would be more people to review the results. As a single researcher, it was a high priority to keep the results manageable in a limited time frame.

1.4 Terminology

As noted in Section 1.1, the information literacy research field is characterised by an abundance of terms, which are often inconsistently used. In order to keep a clear line of reasoning, the choice has been made to keep the terminology limited to *information literacy* and *algorithmic literacy* as much as possible. *Information literacy* is used in the broadest sense and includes all (digital) information literacies, with the exception of algorithmic literacy. The consistent use of the term *information literacy* seemed preferable over using terms like *media and information literacy* or *digital literacies*, both for readability purposes, as well as for placing this thesis more clearly in the tradition of information literacy research. The term *algorithmic literacy* is used for information literacy focusing on algorithms. If sources use other terminology, this is only mentioned if relevant or necessary for the context.

2 Theory – Information literacy in research and practice

In the following chapter theory on information literacy in research and practice will be discussed. This will set a theoretical perspective and will aid in answering the research questions. It includes sections on information literacy and related literacies (Section 2.1), information literacy and librarianship (Section 2.2), and information literacy research (Section 2.3).

2.1 Information literacy and related literacies

With the changing information landscape and the rise of new technologies and media, the number of literacies has grown as well. These literacies are closely related to information literacy as they encompass similar competencies, skills, behaviours, critical ways of thinking, and significance both for the individual information user and society as a whole. Furthermore, the concept of literacy itself, while at its core meaning being able to read and write, has been extended to something much larger: a literate person can critically assess texts (or information) and is empowered to challenge the ideas within (Limberg et al., 2012).

Consequently, the terminology is continuously adapted to fit the focus of the various literacies, leading to a diffuse and growing set of literacies related to information literacy, for example media literacy, media and information literacy, digital literacy, and algorithmic literacy. Although media literacy and digital literacy come from different roots, focusing specifically on media and digital technologies respectively, in the current digital information environment these literacies have become closely related to information literacy. Aiming to encompass the many related aspects, this has led to combinations, plural versions, and more abstract terms, such as media and information literacy (MIL), information literacies, digital literacies, multiliteracies, multimodal literacy, and metaliteracy (Bawden & Robinson, 2022; Haider & Sundin, 2022c; Stordy, 2015). Furthermore, definitions, applications, and use of the terminology is not consistent, making research into a specific literacy challenging (Stordy, 2015; Zarouali, Boerman, et al., 2021).

Bawden and Robinson (2022) stipulated that information literacy, digital literacy, and media literacy could all mean the same thing, namely “[t]he ability to use information effectively, in all formats, in a largely digital information environment” (p. 331). They chose to use *digital literacies* as an umbrella term for these and related literacies, although they also proposed another, new term that they thought might even be more appropriate. However, as “the area is bedevilled by too many terms as it is” (p. 333), they decided to use a more well-known term. Haider and Sundin (2022c) also pointed out that these terms often “appear[ed] to be used interchangeably” (p. 11). As a consequence, the term *media and information literacy* had been introduced and adopted in many public, professional and educational settings. It can be defined as “critical engagement with media and information in digital settings” (p. 13-14).

However, there are notable differences between media literacy and information literacy. According to Haider and Sundin (2022c) the focus on information structures is what discerns information literacy from media literacy. The infrastructure of information is closely tied to library instruction, librarianship, and Library and Information Sciences research. Media literacy on the other hand, is more concerned with media themselves, how they are produced and brought into circulation, how they are accessed, and what their meaning is. There is often a critical approach, investigating power structures in media.

Consequently, information literacy provides a solid base for the examination of the role of algorithms in the modern digital information landscape, viewing algorithms as part of information structures. Nonetheless, the close relation to media literacy is likely to be helpful, providing a broader, critical approach.

2.2 Information literacy and librarianship

The term information literacy was coined in 1974 by Paul Zurkowski in the context of working with ICT in the workplace. Information literacy has been closely tied to librarianship ever since it was adopted by the American Library Association (ALA) in 1989, defining it as a set of abilities regarding recognising a need for information and consequently finding, evaluating and using that information (Bawden & Robinson, 2022).

As Limberg et al. (2012) note, information literacy in the context of librarianship is often viewed as something that is taught. This comes from a long tradition of library instruction, where searching and selecting information were the focus. This has developed further into teaching how users can evaluate sources and use the information that was found.

Building information literacy is supported by international institutions, such as UNESCO (n.d.-a, n.d.-b) and the Council of Europe (2020), and national and international library organisations. Multiple standards and frameworks have been developed and are being used for teaching information literacy. In North America, the Association of College & Research Libraries, a suborganisation of ALA, developed standards for information literacy, which have been transformed into a framework in 2016: the ACRL framework for teaching information literacy in higher education (Association of College & Research Libraries, 2016). In the UK and Ireland, the Society of College, National and University Libraries (SCONUL) has put forward the Seven Pillars of Information Literacy in 1999, which was updated in 2011 and reviewed in 2015 (Goldstein, 2015). Additionally, the International Federation of Library Associations and Institutions (IFLA) supports information literacy through a dedicated section of the organisation, organising projects and events (International Federation of Library Associations and Institutions, n.d.).

The goal of information literacy can be viewed in two distinct ways. One view is that information literacy is about skills and competencies for finding and handling information, which serve as “a basis for lifelong learning in capitalist society” (Haider & Sundin, 2022c, p. 15), where people are taught to be adaptable as workers and consumers in an ever changing information society. The other view focuses on information literacy as a necessity for a democratic society, where citizens not only have skills and competencies to work with

information, but also awareness and critical thinking abilities to be able to participate in democracy (Haider & Sundin, 2022c; Polizzi, 2020). It should be noted that this is also true in the broadest sense of democratic society, where far-right and alt-right media have claimed a space in the current information landscape. Users and makers from these media also benefit from their own increased literacy, which enables them to advance their own anti-democratic message further, potentially including mis- and/or disinformation (Haider & Sundin, 2022c).

2.3 Information literacy research

There are many, sometimes conflicting, ways to view information literacy and to approach studying it, based on the situation and context, time in history, and material in focus (Haider & Sundin, 2022c). Street (1984) introduced two viewpoints on information literacy research: the autonomous model and the ideological model. To this day these models provide a useful way of framing information literacy research (Haider & Sundin, 2022c). In the autonomous model, information literacy is seen as a clearly defined set of skills or competencies. Information literacy in the ideological model, on the other hand, is seen as practices in a sociocultural context (Haider & Sundin, 2022c; Limberg et al., 2012).

These models may result in different approaches of studying information literacy. Two common approaches are the evaluative approach and the explorative approach (Lundh et al., 2013). The evaluative approach is taken when a clear definition of information literacy is used as a starting point. It has a strong normative component, it is something that can be measured, and the desired level or outcome of education can be defined. In contrast, the explorative approach does not start out with a clear definition of information literacy, but describes the concept in the process of studying it. The normative component is less emphasised (Haider & Sundin, 2022c; Lundh et al., 2013).

The evaluative approach echoes the autonomous model, with its focus on a clear definition of what information literacy is, and its interest in norms and measuring. Quantitative research methods correspond well with this approach. The explorative approach, on the other hand, mirrors the ideological model, with its interest in describing information literacy practices in a sociocultural context, and seems to be more suited for qualitative research methods.

Norms or practices?

The normative element in information literacy becomes clear when a list of skills and abilities is used to describe what an information literate person is able to do, often formulated as a number of steps to be followed. It is therefore often used in curricula and policy documents. However, standards with strictly defined sets of skills have also been criticised for being too prescriptive and not taking the context into account. This criticism has led to further developments of standards, such as the ACRL framework (mentioned in Section 2.1), which was created as a replacement of an older set of standards which were more normative (Haider & Sundin, 2022c).

Nonetheless, thinking of information literacy as a set of skills and abilities possessed by information users means that it can be taught and measured in

education, and promoted through policy. As a result, initiatives to increase democracy through information literacy often have a strong normative component (Haider & Sundin, 2022c). The assumption is made that democracy will increase through increased information literacy, although it is unclear how this might work and might actually be a false assumption, especially if information literacy is seen as a set of skills and abilities, following the autonomous model. Haider and Sundin (2022c) use the example of the high literacy rate of the Swedish population in the 17th century: while most people could read, they did not have the high living standards one might expect when assuming high literacy correlates with better living circumstances.

3 Literature review – Algorithmic literacy

In the second edition of Bawden and Robinson's (2022) handbook *Introduction to Information Science*, algorithmic literacy has been included in the section about digital literacy and was defined as "understanding the nature of algorithmic decision making [sic] and its potential for inaccuracy and bias" (p. 337). Its recent inclusion implies the current relevance of the term in the field of Library and Information Sciences. At the same time it shows the difficulties defining this concept, only focusing on algorithmic decision-making and not elaborating on what this understanding might entail. This is not surprising, given that the concept appears to have been around for only about twenty years, and has been used by authors from various academic fields and theoretical backgrounds.

The earliest identified uses of the term *algorithmic literacy* were encountered in the early 2000s. The term was mentioned as describing a way for biologists to increase their algorithmic skills for bioinformatics (Miron & Nadon, 2006), in the context of developing a computer science course (Hazzan & Lapidot, 2004), and in a book chapter discussing new technological literacies where algorithmic literacy was specified as something that was "acquired in computer programming" (Seel & Casey, 2003, p. 39).

Algorithmic literacy was also named on a weblog where the search results of Google and its ranking algorithms were questioned, and a user noted that learning about media and information in school might not be enough: "we now [perhaps] need to teach not only media literacy, but algorithmic literacy as well" (Amy, 2004). In a book review in *Digital Humanities Quarterly*, about a book on digital media by Wardrip-Fruin (2009), the author of the review stated that the book had good ideas about "how one might teach algorithmic literacy across the curriculum without delving into the syntax of any particular programming language" and that "algorithmic thinking is an essential literacy, not just for scholars in the digital humanities ..., but for all educated citizens of the 21st century" (Reside, 2010). Interestingly, Wardrip-Fruin (2009) did not use the term algorithmic literacy or anything similar. He did mention "procedural literacy", which "may help more people understand how computational processes are authored" (p. 214). However, he explicitly stated that the book did not aim to contribute to that, but to something broader.

In these early mentions, two ways of looking at algorithms are apparent: the mathematical/technological view and the sociocultural view. The first viewpoint is demonstrated in the articles about biologists' algorithmic skills, the computer science course, and the new technological literacies. The way algorithms are looked upon can be seen as the textbook definition of an algorithm: a mathematical or computational object consisting of a set of rules or instructions that are to be followed to solve a problem (Dictionary.com, n.d.). Knowledge and skills about the mathematical workings are necessary for this sense of algorithmic literacy.

In the second view, the algorithm is seen as a sociocultural object that a user interacts with. In this understanding of algorithmic literacy, knowledge about mathematical calculations or computer programming is not necessarily relevant for a user dealing with information and media. This view corresponds with the

work of Seaver (2017) on algorithms as culture. The interest in algorithms as sociocultural objects can be traced back to the work of scholars in humanities and social sciences, participating in critical algorithm studies in the first half of the 2010s. In 2015 Gillespie and Seaver produced a reading list for this diverse field, showing the wide academic interest in this topic up until that point (Gillespie & Seaver, 2015; Moats & Seaver, 2019). In this thesis the sociocultural view of algorithms is most relevant, although the technological view is used in addition to the sociocultural view in some cases, as will become clear in the Chapter 5, where the results are discussed.

While there have been multiple studies into algorithmic literacy, as will be presented in this thesis, there is no clear overview of the state of knowledge. This problem has also been recognised by Oeldorf-Hirsch and Neubaum (2022), which they aimed to address in their literature review about algorithmic literacy. In this review they aimed to define the concept, map existing issues, and find areas for future research. They encountered problems with terminology when researching algorithmic literacy, similar to the findings in this thesis. One of their recommendations was to use only this term in future research.

In many senses their work is quite closely related to the motivation and goals of this thesis. However, their method was not clearly defined, which made the results and conclusions not very transparent or reproducible. Additionally, there was no specific interest in information literacy or related literacies, which is a key part of this thesis. Furthermore, as the article has not been published in a peer-reviewed journal, it is not part of this scoping review.

4 Method

In this thesis the scoping review is used as the method. A scoping review is a literature review belonging in the realm of documentary research methods. Other categories of documentary research include systematic reviews, meta-analyses, secondary data research, historical and archival research, and policy research (Tight, 2019). The scoping review entails a systematic, reproducible way of working and covers a topic broadly and comprehensively. This type of review aims to give an overview of what research has been done, to summarise and disseminate this knowledge, and to identify knowledge gaps and gather pointers for further research. Scoping reviews are also a valuable way for scholars to quickly get informed about an emerging topic, or a topic or research domain they are not very familiar with (Arksey & O'Malley, 2005; Paré et al., 2015; Tight, 2019).

The scoping review focuses on a broad research question, in which studies are examined that use various methods and theories. This way a broad scope of knowledge on a specific topic can be covered (Arksey & O'Malley, 2005). This makes it very useful for social sciences where many different methods and theories may be used to study the same subject.

The procedure of a scoping review is always explicitly described, aiming to make the study transparent and reduce the possibility of bias, while also making the study reproducible and extensible. In order to accomplish that in this study, the methodological framework of Arksey and O'Malley (2005) is followed: (1) identification of the research question; (2) identification of relevant research papers; (3) selection of research papers; (4) sorting and mapping of the selection; (5) summarising and reporting of the findings. These five stages are further described below.

This thesis follows the guidelines of PRISMA-ScR (Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews; Tricco et al., 2018). According to these guidelines the reporting of a scoping review should include twenty necessary items, while two items are optional. The guidelines have been developed to standardise documentation on scoping reviews and hence makes this method more transparent, more easily replicable, and of higher quality. While the guidelines were developed for scoping reviews in health research, they have also been adopted by Library and Information Sciences researchers (e.g. Butler & Calcagno, 2020; Murphy et al., 2021; Stapleton et al., 2020a). Item 27 about funding is not applicable to a thesis, thus was excluded in this work (for all items, see Tricco et al., 2018).

Further recommendations with regard to database selection specifically for Library and Information Sciences have been proposed by Stapleton et al. (2020b). This has been discussed in Section 1.3, in the paragraph on databases.

4.1 Identification of the research question

Algorithms have become ubiquitous in the daily information landscape: they shape the feeds on social media (e.g. Swart, 2021), the results from search engines (e.g. Cotter & Reisdorf, 2020), and the recommendations from

streaming services (e.g. Kapsch, 2022), but also support decision-making or even perform this function automatically (e.g. König, 2022). Their workings are often obscured and of propriety nature, making it difficult for users to understand when and how algorithms are influencing their feeds, search results, recommendations, and other digital interactions. Therefore it is key for information users to have knowledge and skills regarding the influence of algorithms on the way this information is found, used, shared, collected, and disseminated – or concealed.

From the Library and Information Sciences point of view this could be done by developing information literacy further with the concept of algorithmic literacy to incorporate knowledge and skills related to algorithms. Other related literacies appear to be relevant as well. Consequently, the concept has not been defined uniformly, the terminology used is diverse and inconsistent, and there are multiple approaches to view and study algorithmic literacy. Additionally, it is unclear what research has been done and what is known about algorithmic literacy. A review of existing empirical evidence and conceptual thinking about this topic is thus necessary. This has led to the following main research questions and sub questions (as previously mentioned in Section 1.1):

1. What is known about the concept of algorithmic literacy?
 - How is it related to information literacy and other related literacies?
 - What terms are being used to describe algorithmic literacy and related topics?
2. How is algorithmic literacy being studied?
 - What do we know about algorithmic literacy from these studies?

4.2 Identification of relevant literature

Literature relevant to this scoping review was limited to peer-reviewed journal articles written in English published between 2018 and April 2022. Articles that were in press at the moment of writing, but had been peer-reviewed and published online by the publishing journal were included in this study in order to have results as up to date as possible.

Relevant literature was searched in the databases LISA (Library & Information Science Abstracts), LISTA (Library, Information Science & Technology Abstracts), ERIC ProQuest (Educational Resources Information Center, as provided by ProQuest), and Scopus. LISA and LISTA were selected based on their relevancy for Library and Information Sciences and ERIC for education, as this is a field that is closely related to literacies research. A broad scope was maintained by using Scopus as a large, multidisciplinary scientific database to identify any relevant articles from other fields.

Query development

Each database was searched with the same query. In order to optimise the query, it was developed iteratively, by performing preliminary queries and investigating the scope and nature of the results while considering the constraints in time. An iterative nature of working is distinctive of the scoping review (Arksey & O'Malley, 2005).

The preliminary queries included different timeframes and different search strings. An initial analysis of the period 2018-2022 showed a growth in the number of articles on this topic, thus indicating an interesting period to study. At the same time, the number of results amounted to a manageable workload for one researcher. Hence this period was chosen.

The preliminary search string was very narrow and searched only for the term *algorithmic literacy*, and possible variants such as *algorithmic literacies* and *algorithm literacy*, by using phrase search and truncation: "algorithm* literac*". This resulted in highly relevant results. However, after an initial analysis of the results, it became clear that it likely also omitted relevant articles which did not use the exact term *algorithmic literacy* or a variant. It appeared that the use of the term might be somewhat problematic, as will be investigated further in this study.

An attempt to capture all terms relevant to algorithmic literacy, by searching for other relevant terms in addition to *algorithms* and *literacy*, yielded many results. This made it unfeasible to examine them all, while there was also no guarantee that all relevant terms had been identified. Therefore, the strategy was chosen to search for articles mentioning both algorithms and literacy, but not necessarily as a phrase. Again variants were accounted for by using truncation with the query algorithm* AND literac*. Searching for these terms presumed that any relevant articles would contain both these terms. It would include articles mentioning other types of literacies that might be relevant (e.g. media and information literacy, data literacy) and would thus not exclude any articles that did not mention algorithmic literacy literally. A disadvantage was that it would also include articles that mentioned other types of literacies that were likely not relevant to the research question (e.g. financial literacy).

In the databases, the option was set to search for the terms in the title, abstract or keywords. The assumption was made that any article on algorithmic literacy would have the search terms in one or more of the queried parts, as these are the most informative parts of an academic article regarding the identification of the topic. The query was purposely not done as a full-text search. This was practical on multiple levels, as not all databases allowed full-text searching and full-text searching would take more time to perform. Additionally, it would likely result in many items which would need more time to inspect. Moreover, these results would likely contain relatively more irrelevant results, as these would also include items with a single appearance of one of the terms anywhere in the text.

The databases were queried on 9 April 2022, searching for the terms algorithms and literacy in the title, abstract or keywords. The search was limited to peer-reviewed academic articles in the English language published in journals from 2018 onwards. The settings needed to be adjusted accordingly based on the functionality of the database. For example, Scopus was queried with the following search string:

```
TITLE-ABS-KEY ( algorithm* AND literac* ) AND PUBYEAR > 2017
AND ( LIMIT-TO ( SRCTYPE , "j" ) ) AND ( LIMIT-TO ( DOCTYPE ,
"ar" ) ) AND ( LIMIT-TO ( LANGUAGE , "English" ) )
```

The references of the results were added to the open-source reference manager Zotero version 6. Any double entries from the different databases were removed through the process of deduplication. This was done in Zotero using its ‘Duplicate Items’ function, which gave an overview of any items that might be duplicates and offered the possibility to merge those items per set of duplicates. This granted the researcher utmost control of the process while increasing the speed compared to manual deduplication.

Complementary methods

Arksey and O’Malley (2005) mentioned three complementary methods for finding relevant literature: (1) searching reference lists of relevant articles, (2) searching in key journals by hand, and (3) inquiring at relevant networks, organisations and conferences. However, these complementary searching methods are not always used in practice. Some scoping reviews in Library and Information Sciences reported only using databases to identify relevant literature (e.g. Boruff & Harrison, 2018; Kjellberg et al., 2016). Others mentioned examining the reference lists of relevant articles (e.g. Stapleton et al., 2020a; Urban, 2019), and hand-searching specific journals when the chosen databases did not cover all relevant journals (Stapleton et al., 2020a).

In the present study, the references in the included articles were examined to identify other relevant literature, especially by inspecting the sources used to define algorithmic literacy, if the term was present in the article. Hand-searching of key journals was not done as the scope of the queried databases was expected to be sufficient. Relevant networks or organisations were also not specifically consulted, as this method was not encountered in other scoping reviews, and thus appeared to be not very relevant for this research field at this point in time.

4.3 Selection of articles

An overview of the workflow and the results of the identification and selection process of the articles is shown in a PRISMA 2020 flow diagram (Page et al., 2021) in Figure 1. The query of the selected databases resulted in 33 (in LISTA) to 284 records (in Scopus) per database. After deduplication 100 unique records remained, of which the title, abstract and keywords were screened. This was the first step to make a preliminary selection. All articles that used the term *algorithmic literacy* were included in the selection. Any articles that did not contain this term, but were potentially relevant based on the title, abstract or keywords, were included in the preliminary selection. Any articles that were clearly not relevant for the review, again based on the title, abstract or keywords, were excluded. This was the case if an article focused only on a type of literacy that was not related to algorithmic literacy, for example literacy meaning reading and writing, and financial literacy. An exception was made for articles where algorithmic literacy might be a relevant concept beside another literacy that was in focus. This was the case if knowledge and skills regarding algorithms was mentioned in connection to the other literacy.

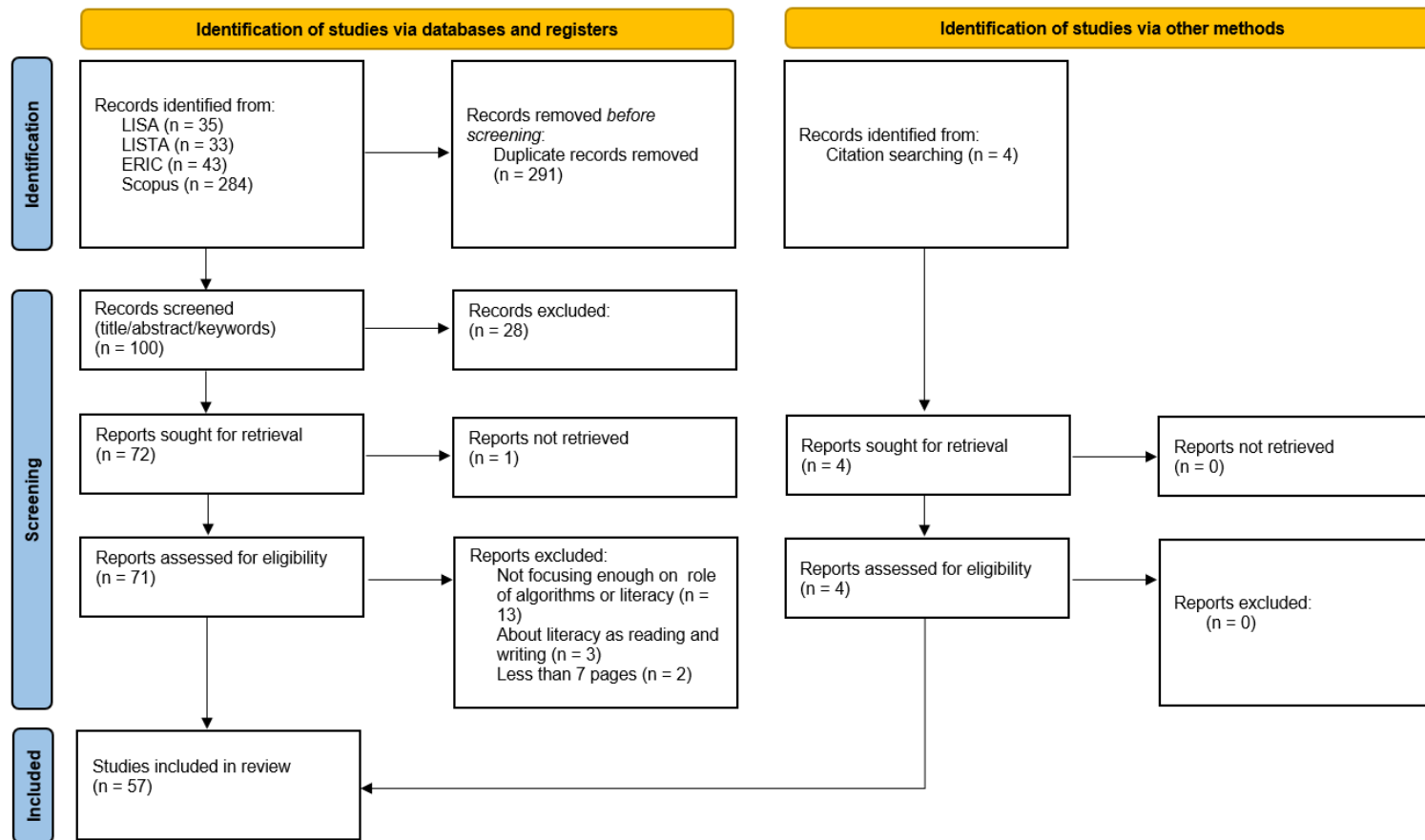


Figure 1
PRISMA 2020 flow diagram (Page et al., 2021) describing the workflow and results for identifying and selecting relevant articles

Articles were also excluded if algorithms were only described in the computational sense, as these articles reported on studies where algorithms were only involved for computations. These articles described for example a type of algorithm by mentioning its name (e.g. k-nearest neighbour) or the algorithm family it belonged to (e.g. evolutionary algorithms), or mentioned a typical outcome of an algorithmic process (e.g. a prediction model). If it was unclear if an article was relevant based on the title, abstract and keywords, the article was included in the preliminary selection in order to examine the full text at a later stage.

During the preliminary selection process 28 articles were excluded, either for formal reasons (not in English) or for subject matter (not related to algorithmic literacy). When this process was complete, the full-text articles were retrieved. Any article that could not be accessed through the database subscriptions of the University of Borås or the open web were excluded from the selection. One of the articles could not be retrieved and was therefore excluded. This led to a selection of 71 full-text articles.

The next step involved examining the retrieved articles. A minimum article length of seven pages was also determined, to exclude any short texts that did not discuss algorithmic literacy in sufficient depth, such as editorials or short commentaries. Two articles were excluded on these grounds. Following this, the complete text was examined. If the term *algorithmic literacy* was mentioned anywhere in the article's text, it was included in the final selection. All remaining articles were examined further, and were excluded if they did not focus on algorithms or literacy enough (13 articles were excluded for this reason), or if they focused on literacy as reading or writing (3 articles were excluded). As a final step the selection was read in full. Additionally, another four relevant articles were identified by examining the references of articles included in the review. This led to a total of 57 articles.

4.4 Data charting

The articles in the final selection were analysed in order to find any common themes, methods and other characteristics. Excel was used to record the articles' bibliographical information and details about the content. For each article the author's information (including country and research domain) and journal's information (including title and subject area) were recorded as bibliographical information. The choice of which bibliographical features should be recorded was guided by other scoping reviews in the field of Library and Information Sciences (see Section 1.2). Additionally, information regarding the article's content was noted. The choice of which content-related features to record was guided by the SPIDER framework. The SPIDER framework is a tool for analysing a research question, and thus a study, by identifying the Sample (S), the Phenomenon of Interest (PI), the Design (D), the Evaluation (E), and the Research type (R). Using a framework to analyse the research question was adopted from the systematic review method, where often PICO (Population, Intervention, Comparison, Outcome) is used for analysis of quantitative research. SPIDER is seen as more suitable than PICO for qualitative and mixed methods research, although quantitative research may be analysed as well (Cooke et al., 2012). This made it a suitable framework for a scoping review, where different types of studies might be included.

The SPIDER framework was adapted for this review. The Sample (S) was interpreted as referring to the subjects in the study, the Phenomenon of Interest (PI) as the topic of the study, the Design (D) as the research design and any theories used, the Evaluation (E) described the results or outcomes, and the Research type (R) answered the question whether the research used quantitative, qualitative or mixed methods.

Furthermore, the definition of algorithmic literacy and its position within the literacies were added as features specific to the context of this study. Also, any themes and knowledge gaps were recorded. Since these last two items were contextual to the scoping review as a whole, the process of determining these was iterative in nature. No formal critical appraisal of the individual sources was done.

4.5 Summarising and reporting of the findings

The findings were first summarised based on their bibliographical information, as described in Section 4.4. Then the definitions of algorithmic literacy were examined. After this a thematic analysis was made, also based on the features described in Section 4.4. The analysis resulted in four themes: (1) the necessity of algorithmic literacy, (2) algorithm awareness as the basis for algorithmic literacy, (3) teaching and learning algorithmic literacy, and (4) studying algorithmic literacy. The results of these analyses can be found in Chapter 5, and an overview of the identified knowledge gaps is given in Section 6.3.

5 Material and results

In the following sections the selected material and results are presented. The first sections give an overview of the bibliographical details: the journals and articles (Section 5.1), the authors (Section 5.2), the keywords (Section 5.3), and the research methods, subjects, their geographical locations and algorithmic systems in focus (Section 5.4). After this, various definitions of algorithmic literacy are examined, and associated concepts and literacies are identified (Section 5.5). The following sections include thematic analyses: the necessity of algorithmic literacy (Section 5.6), algorithm awareness as the basis of algorithmic literacy (Section 5.7), and teaching and learning algorithmic literacy (Section 5.8). This is followed by an in-depth exploration into how algorithmic literacy is being studied (Section 5.9).

5.1 Journals and articles

The following section aims to give insight into what journals and research areas are occupied with algorithmic literacy research, and if any trends over time can be identified.

Subject areas

The 57 articles appeared in 44 different journals, seven of which have published more than one relevant article: the *Journal of Media Literacy Education* (five articles), *Information, Communication & Society* (four articles), *Computers and Composition* (three articles), *AI & Society* (two articles), the *International Journal of Communication* (two articles), the *Journal of Business Ethics* (two articles), and the *Journal of Documentation* (two articles).

The most common main subject area of the journals was Education (13 journals), Communication (ten journals), and Library and Information Sciences (seven journals). See Figure 2 for these and further subject areas. The subject areas were analyzed with Scopus's source details (Scopus, n.d.), using the first named subject area. Two journals were not indexed by Scopus. However, from the title and article content these were estimated to belong to the Library and Information Sciences field (*Pennsylvania Libraries: Research & Practice* and *Legal Information Management*).

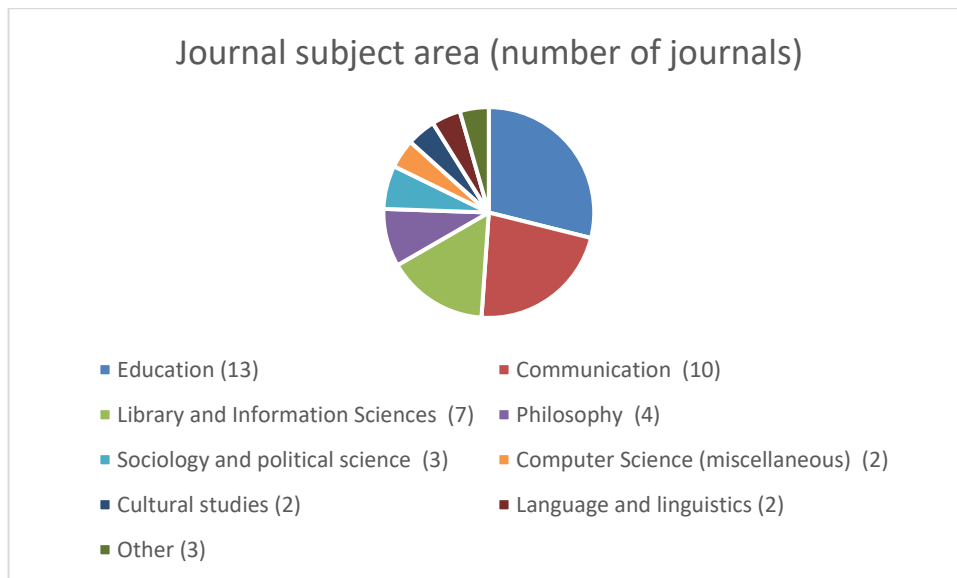


Figure 2
Journal subject areas with number of journals between brackets

The fact that Education and Library and Information Sciences were identified as two of the main subject areas was not surprising, given the fact that three databases specialised in these exact subjects. These two areas also cover research on media literacy and information literacy. The fields of Communication and Language are also related in the sense that they also study literacies, and likely have some overlap with these two areas. Computer Science is related to the Information Science part of Library and Information Sciences. Philosophy, sociology and cultural studies might be related on a higher level, for instance when discussing ethics in relation to algorithms and the role of literacy. Hence, the graph gives a good indication of the multidisciplinary nature of the topic of algorithmic literacy.

Year of publication

To identify any trends, the publication dates of the articles were examined. The date the article was published in a particular issue was used as the publication date. If an article had not yet been published in an issue, but only as an advance online publication on the journal's website, the year of online publication was used.

In Figure 3 an overview is given of the number of articles that have been published per year, including how many contained algorithmic literacy as a term. Most articles were published in 2021: 21 articles. This shows strong growth compared to the years before: from two articles in 2018, to nine articles in 2019 and 13 articles in 2020. At the moment of querying the databases (9 April 2022) the total for 2022 was 12 articles. This is likely not the full number of relevant articles published this year, as only articles published and indexed before the date of the search in the databases are considered.

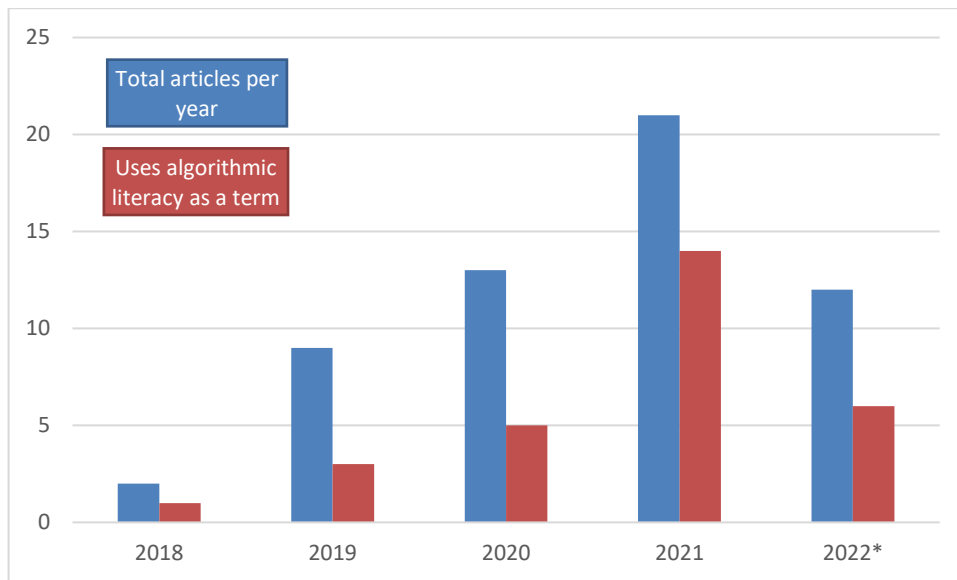


Figure 3

Total number of articles published per year and number of articles that use the term algorithmic literacy. Note that only articles indexed by the databases up until 9 April 2022 are included in these numbers.

*) Two articles from 2022 have only been published as an advanced online publication and not yet in an issue. These articles have been included in these numbers as if they were published in said years.

The growing interest in this concept can be observed through the increasing number of articles being published on this topic. It can also be noted that the term algorithmic literacy is only used in a part of the articles, but that this number is growing relatively. This might indicate that the term is becoming more adopted. Furthermore, the fact that a substantial part of the articles does not use the term algorithmic literacy, also hints at the diverse terminology used in this field. In the years 2019-2021 a shift can be noted, as the term algorithmic literacy was used considerably more, from being used in less than half in 2019 and 2020, to being used in almost two thirds of the articles in 2021. At the moment of finalising this thesis (October/November 2022) at least six more relevant articles have been indexed by Scopus that use algorithmic literacy as a term (result on 21 October 2022 when searching for English-language peer-reviewed academic articles with the query "algorithm* literac*"). However, no definite conclusion can be drawn yet for 2022, and continuing research is needed to clarify if this is an upgoing trend over a longer period of time.

5.2 Authors

In this section the authors are examined further. This aims to give insight into where research activities take place by determining the country of the institution an author is associated with, what level of collaboration among authors can be distinguished, and which research areas authors are active in.

A total of 127 unique authors from institutions in 19 countries were identified; mainly from Europe (66 authors from 11 countries) and North America (39 authors from two countries), and in a lesser extent from Asia (20 authors from

five countries) and Oceania (two authors from two countries). No authors from South American or African institutions were encountered. The largest amount of authors were affiliated with an institution from the USA. In Europe, most authors were from Switzerland, Germany, Norway, and The Netherlands. In Table 1 an exact overview per country can be found.

Table 1
Numbers of authors per country of institution

Europe	Belgium	4
	Denmark	2
	Finland	5
	Germany	12
	Netherlands	10
	Norway	11
	Russia	1
	Sweden	3
	Switzerland	13
	UK	5
North America	Canada	8
	USA	31
Asia	Hong Kong	6
	Israel	4
	Japan	2
	Kazakhstan	5
	UAE	3
Oceania	Australia	1
	New Zealand	1

Most authors have written one article, whereas ten authors have written two: Haider, Hargittai, Helberger, Shin, Sundin, Tedre, Valtonen, Vartiainen, De Vreese, and Zarouali. Some of these authors wrote their two articles with the same co-author(s). This is true for Haider and Sundin, De Vreese and Zarouali, and Tedre, Valtonen and Vartiainen.

The majority of the articles have been written by a maximum of three authors (one author: 19 articles; two authors: 18 articles; three authors: ten articles), although teams of up to seven authors have been noted. Most author duos are from the same country, but not necessarily from the same institution. In teams of three or more authors, more international collaboration can be noted, although the majority is undertaken on national level. International collaboration happened in some cases between authors from countries which are geographically close, such as a collaboration between Dutch and German authors (Dogruel et al., 2022), and in other cases between authors who were geographically dispersed, such as a collaboration between authors from Hong Kong, New Zealand and Norway (Ku et al., 2019). Again, similar to the teams of two authors, most author teams of three or more people consisted of members who belonged to institutions from the same country, but not necessarily the same institution. Therefore, it can be concluded that collaboration is important in this field of research. It has primarily taken place

on a national level, although international collaboration has also been undertaken.

To discern the research areas where researchers are interested in the topic of algorithmic literacy, the research area of the first author of each article was identified. This was based on the information given in the article or, if this was unclear, by searching online. Most first authors' research areas fell into one of three groups: education (including pedagogy and educational psychology; 14 first authors), communication (including media, journalism, English and writing; 16 first authors), and Library and Information Sciences (including Information Systems and Computer Science; 12 first authors, including five articles written by librarians (Gardner, 2019; Garingan & Pickard, 2021; Kiester & Turp, 2022; O'Hara, 2021; Ridley & Pawlick-Potts, 2021). Other research areas included business, information law, and health.

5.3 Keywords

An analysis of the keywords helps to better understand how the relevant articles are described and what concepts are being studied and discussed. The keywords were normalised for variation in spelling, grammar (e.g. *algorithm awareness* and *algorithmic awareness*), and number (singular/plural), and combined if the meaning is the same (e.g. *algorithmic decision-making* and *algorithm-based decision-making*). As an exception to this process the terms *digital literacy* and *digital literacies* were not combined. As shown by Limberg et al. (2012), various terms have been used in the information literacy discourse, aiming to capture changes or differences more adequately. This can be observed in the fact that both *digital literacy* and *digital literacies* are encountered, alluding to a difference in meaning. This was also made clear by Bawden and Robinson (2022), who explicitly chose to use digital literacies as an umbrella term including information, media, and digital literacy. It should be noted that digital literacies was the only keyword that referred to any literacy in the plural form.

Five articles did not contain any keywords. The 52 remaining articles had a total of 297 keywords, 197 of which were unique after normalisation. These keywords are represented in Table 2, 3, and 4, and Figure 4. The large amount of unique keywords alludes to the diversity of terminology being used, but also to the various topics being studied. In the following sections the keywords that occurred multiple times are analysed first, followed by an analysis of the keywords that occurred once.

Multiple occurrences

Less than one-fifth of all keywords occurred more than once: 35 of the total of 197 keywords. These are shown in Table 2. These frequently occurring keywords can be divided into three groups: those that refer to 1) different literacies and education, to 2) various algorithmic terms, including technological concepts and concepts related to the social aspects of algorithms, and to 3) media. The first and the third group, referring to literacies and to media, partly overlap. An overview of the keywords in these three groups is given in Table 3.

Table 2
Keywords appearing more than once, descending order

<i>Keyword(s)</i>	<i>Number of occurrences</i>
algorithms	19
algorithmic literacy	14
media literacy	7
digital literacy; information literacy; algorithm awareness	6
artificial intelligence; social media	5
transparency	4
accountability; AI literacy; audience; digital divide; digital literacies; fairness; machine learning; media education; trust	3
algorithm bias; algorithmic culture; algorithmic decision-making; critical media literacy; critical thinking; digital inequality; disinformation; education; ethics; explainability; infrastructure; Internet skills; literacy studies; news; news literacy; pedagogy; media and information literacy	2

Table 3
Keywords appearing more than once; grouped thematically, and presented alphabetically per theme

<i>Literacies and education</i>	<i>Algorithms and algorithmic concepts</i>	<i>Media</i>
AI literacy	<i>Keywords containing 'algorithm'</i>	critical media literacy
algorithmic literacy	algorithms	media and information literacy
algorithmic methodological and mathematical literacy and methodological literacy	algorithm awareness	literacy
critical media literacy	algorithm bias	media education
critical thinking	algorithmic culture	media literacy
data literacy	algorithmic decision-making	news
digital literacies	algorithmic skills	news literacy
digital literacy	algorithmic credibility	social media
education	algorithmic knowledge	
functional literacy	algorithmic platforms	
ict literacy	critical algorithm studies	
information literacy	<i>Technological concepts</i>	
internet skills	artificial intelligence	
literacy	machine learning	
mathematical literacy	<i>Sociocultural concepts</i>	
media and information literacy	accountability	
media education	digital divide	
media literacy	disinformation	
news literacy	ethics	
pedagogy	explainability	
	fairness	
	infrastructure	
	transparency	
	trust	

As noted, the largest group of frequent keywords referred to literacies and education. The second most frequent keyword (after *algorithms*) in the review was, not surprisingly, *algorithmic literacy* (14 times), followed by *media*

literacy (seven times), *digital literacy* (six times), and *information literacy* (six times). Other keywords naming different literacies were *AI literacy*, *digital literacies*, *critical media literacy*, *media and information literacy*, *news literacy*, *algorithmic methodological and mathematical literacy*, *data literacy*, *functional literacy*, *ict literacy*, *literacy*, *mathematical literacy*, and *methodological literacy*. Further keywords related to education were *media education*, *critical thinking*, *education*, *pedagogy*, and *internet skills*.

Algorithms and algorithmic concepts also appeared frequently as (parts of) keywords. As noted before, the term *algorithms* was found most frequently (19 times). Other keywords containing *algorithm* in some form were *algorithm awareness*, *algorithm bias*, *algorithmic culture*, *algorithmic decision-making*, *algorithmic skills*, *algorithmic credibility*, *algorithmic knowledge*, *algorithmic platforms*, and *critical algorithm studies*. The keywords *artificial intelligence* and *machine learning* referred further to technological aspects of algorithms.

Social aspects of algorithms were also encountered. This could be noticed in the following keywords: *transparency*, *accountability*, *digital divide*, *fairness*, *trust*, *ethics*, *explainability*, *disinformation*, and *infrastructure*. This last term was put in this category as this seemed to refer to algorithms as infrastructure and the power aspect in information flows.

The group containing keywords referring to media included keywords as *social media* and *news*, and had a clear overlap with the first group with the keywords *media literacy*, *critical media literacy*, *media and information literacy*, *news literacy*, and *media education*.

Single occurrences

The majority of the keywords, 162 of 197 unique keywords, occurred only once. Thus an analysis of these keywords might reveal more aspects of the broad scope of studies on algorithmic literacy. To this end a word cloud was created using Voyant Tools, which can be seen in Figure 4 and via the link in the caption. The tool analysed and visually presented the frequency of each individual word in the various keywords, which might consist of multiple words. The size of a word indicated its frequency in the set of keywords. This can be viewed more closely when examining the image via the link.

Table 4
Keywords appearing once; grouped thematically, and presented alphabetically per theme

<i>Literacies, education, and research</i>	<i>Algorithms and algorithmic concepts</i>	<i>Media</i>	<i>Library and Information Sciences</i>
analysis arts critical discourse epistemological folk journalism mathematical methodological research studies theory writing	<i>Technological concepts</i>	Facebook Instagram Overwatch Wikipedia	information libraries knowledge use seeking PubMed
	AI algorithmic bots computational data digital online platforms software technology		
	<i>Sociocultural concepts</i>		
	agency impact legal misinformation personalization policy surveillance		

While the term *media* was a frequent word, and was thus large in this word cloud, the group containing media related keywords was still small, although it can now be extended with names of digital services that use algorithms: *Instagram*, *Overwatch*, *Wikipedia*, and *Facebook*. As a fourth group Library and Information Sciences could be added, with terms as *information*, *libraries*, *knowledge*, *use*, *seeking*, and *PubMed*, although these terms could also be added to the larger literacy and education group.

This multiplicity in keywords, both the single and the multiple occurrences, alludes to the problem of describing the concept of algorithmic literacy in a clear and consistent manner. The following terms could be seen as (near) synonyms to algorithmic literacy: AI literacy (Eguchi et al., 2021; Wiljer & Hakim, 2019; Yang, 2022), algorithmic skills (Hargittai et al., 2020; Klawitter & Hargittai, 2018), and algorithmic knowledge (Cotter & Reisdorf, 2020).

Furthermore, based on this keyword analysis, it becomes clear that the concept is placed in at least three literacy traditions or a combination thereof: information literacy, media literacy, and digital literacy/literacies, including data literacy and ict literacy. The term “algorithmic methodological and mathematical literacy”, from the article by Astambayeva et al. (2021), is complicated both in terms of length and meaning. This is not a common term but given the fact that algorithms are named specifically as part of this literacy, plus the authors’ use of literature about information literacy, the conclusion was drawn that this term also encompasses algorithmic literacy in some way.

5.4 Research methods, subjects, and algorithmic systems

In order to get an understanding of what type of research has been done on algorithmic literacy, an overview was made of all included articles. This included what subjects were being studied, where they were from (if relevant), and what algorithmic systems were in focus. Which articles used the term algorithmic literacy was also noted. A division was made between research articles and other types of articles, such as theoretical articles and project reports. This division might give insight into whether the current state of knowledge leans more towards the theoretical side or more to the empirical side. In Appendix A an overview of all included articles can be found.

Types of research

Articles that contained an introduction, method section, results section and discussion/conclusions section were counted as empirical research articles (Bryman, 2016). When examining the articles in this way, 34 could be identified as empirical research articles, of which 14 used quantitative methods, 17 used qualitative methods, and three used mixed methods. The additional 23 articles could not be categorised as empirical research articles. Most of these articles were of theoretical nature. There were also some other types, such as essays, commentaries and project reports. This information was based on the journal's information or similarities to other articles in that category. Details on which category each article was placed in can be found in Appendix A.

Methods

In the empirical studies a number of different methods were encountered. The quantitative studies all employed surveys, sometimes in an experimental design (Astambayeva et al., 2021; Brodsky et al., 2020; Krügel et al., 2022), or a quasi-experimental design (Fouquaert & Mechant, 2021; Shin, 2021). Zarouali, Boerman, et al. (2021) supplemented their study with structured interviews. The qualitative studies mostly made use of (semi-structured) interviews (Bakke, 2020; Bhatt & MacKenzie, 2019; Haider & Sundin, 2022a, 2022b; Hargittai et al., 2020; Jones, 2021; Klawitter & Hargittai, 2018; S. Robinson et al., 2021; Swart, 2021), participant observations (Bakke, 2020; Bhatt & MacKenzie, 2019; Gallagher, 2020; S. Robinson et al., 2021; Svendsen et al., 2022), discourse analysis (S. Robinson et al., 2021; Svendsen et al., 2022; Trammell & Cullen, 2021), and thematic analysis (DeVito, 2021; Haider & Sundin, 2022a, 2022b; Hargittai et al., 2020; Jones, 2021; Kapsch, 2022; Koenig, 2020; Marlatt & Sulzer, 2021; S. C. Robinson, 2020; Trammell & Cullen, 2021). Not surprisingly, the mixed method studies worked with a combination of the methods mentioned above.

Subjects

As may be expected in the realm of social studies, humans were the subjects of most studies. They ranged from participants of national surveys, (Smythe et al., 2021; Zarouali, Boerman, et al., 2021; Zarouali, Helberger, et al., 2021) and samples from general groups of adult internet users (Bakke, 2020), to samples of specific groups of users such as young people (Haider & Sundin, 2022a, 2022b; Ku et al., 2019), creative entrepreneurs (Klawitter & Hargittai, 2018), gamers (Trammell & Cullen, 2021), LGBTQI+ people (DeVito, 2021), health

care professionals (Wiljer & Hakim, 2019), journalists (Bastian et al., 2019), and job seekers (Pethig & Kroenung, 2022). University students were also common subjects (Bhatt & MacKenzie, 2019; Gallagher, 2020), including students of medicine (Kampa & Balzer, 2021), psychology (Brodsky et al., 2020), software engineering (Bogina et al., 2022), information science (Kapsch, 2022), communication (Koenig, 2020), and education (Astambayeva et al., 2021; Marlatt & Sulzer, 2021). Children in kindergarten, primary and secondary school were not encountered as subjects in any of the research articles, although two projects reports and two theoretical articles have been written about algorithmic literacy for (young) children (Eguchi et al., 2021; Valtonen et al., 2019; Vartiainen et al., 2020; Yang, 2022).

In rare cases the studies' subjects were not humans, such as in the work of Jiang and Vetter (2020), who undertook a document analysis of documentation of Wikipedia algorithms, and the work of S. C. Robinson (2020), who examined policy documents of Scandinavian governments by content analysis and quantitative keyword analysis.

Subjects' geographical locations

Most articles focused on subjects from North America or Europe. The subjects were mainly from the USA (Bakke, 2020; Brodsky et al., 2020; Cotter & Reisdorf, 2020; DeVito, 2021; Gallagher, 2020; Gardner, 2019; Klawitter & Hargittai, 2018; Koenig, 2020; Krügel et al., 2022; Marlatt & Sulzer, 2021; Pethig & Kroenung, 2022; S. Robinson et al., 2021; Shin, 2021), Scandinavia (Gran et al., 2021; Haider & Sundin, 2022a, 2022b; Kapsch, 2022; S. C. Robinson, 2020; Svendsen et al., 2022; Valtonen et al., 2019), and Germany (Dogruel et al., 2022; Hargittai et al., 2020; Kampa & Balzer, 2021; Smythe et al., 2021). Few articles focused on Asian countries or Oceania and none studied subjects from South America or Africa. The geographical locations of the subjects were quite similar to those of the researchers. However, sometimes there was a wider view: when researchers studied a global population (S. Robinson et al., 2021), or subjects from different countries than the researchers themselves were located in. This results in inclusion of subjects from Bosnia, Serbia, Hungary (Hargittai et al., 2020), and Spain (Bogina et al., 2022). Interestingly, while there were 13 authors from a Swiss institution (see Table 1), none of the studies focused on subjects from Switzerland.

Algorithmic systems in focus

Around half of the studies focused on algorithmic systems in a broad sense (29 articles), while the other half focused on specific types of systems or platforms: mainly news media and social media (Brodsky et al., 2020; Cohen, 2018; Fouquaert & Mechant, 2021; Kapsch, 2022; Klem et al., 2019; Ku et al., 2019; S. Robinson et al., 2021; Shin, 2021; Swart, 2021), but also search engines (Bakke, 2020; Bhatt & MacKenzie, 2019; Cotter & Reisdorf, 2020; Svendsen et al., 2022), and streaming services and recommender systems (Claes & Philippette, 2020; Kapsch, 2022; Shin et al., 2022).

Notably, most studies focused on algorithmic systems that people use in their private lives. This can also be concluded from the keyword analysis in Section 5.3 and Table 4, where at least three out of five brand keywords refer to services probably mostly used in private: Facebook, Instagram, and the videogame Overwatch. Wikipedia could also be counted in this group,

although it probably also has a large educational user group. PubMed, a major database for medicine and health sciences, is the fifth brand keyword, and led to the small group of studies into algorithmic systems for professional use. Besides a study focusing on PubMed’s new ranking algorithm (Kiestler & Turp, 2022), this group includes a number of studies related to (micro)work (Smythe et al., 2021), HR (Leicht-Deobald et al., 2019; Pethig & Kroenung, 2022), and entrepreneurship (Klawitter & Hargittai, 2018).

5.5 Algorithmic literacy: definitions and literacies

As noted in Section 1.1 and Section 4.1, the concept of algorithmic literacy is not discussed in a consistent and uniform way, and the term is not always used verbatim. To get a better view of this concept the articles using this term are examined more closely. What is algorithmic literacy according to the authors who use this term? How do they define it, if at all? Furthermore, the question of where algorithmic literacy can be placed in the literacies landscape is examined, including observations from articles not using the term literally.

In 29 articles the term algorithmic literacy is used, see Appendix A. In 22 articles the term appeared in the title, abstract or keywords, and in seven articles the term was mentioned only in the body text. Sometimes the term was further specified, as was the case with “critical algorithmic literacies” (Trammell & Cullen, 2021), “algorithmic news literacy” (S. Robinson et al., 2021), “consumers’ algorithmic literacy” (Helberger et al., 2020), and the previously mentioned “algorithmic methodological and mathematical literacy” (Astambayeva et al., 2021). This shows how some authors aimed to describe the type of literacy they studied even more precisely, which is not uncommon in information literacy research, as noted by Bawden and Robinson (2022).

Definitions

An extensive definition of algorithmic literacy came from the conceptual article by Ridley and Pawlick-Potts (2021). After studying literature on information and digital literacy they produced the following definition:

- Algorithmic literacy is the skill, expertise, and awareness to
- Understand and reason about algorithms and their processes
 - Recognize and interpret their use in systems (whether embedded or overt)
 - Create and apply algorithmic techniques and tools to problems in a variety of domains
 - Assess the influence and effect of algorithms in social, cultural, economic, and political contexts
 - Position the individual as a co-constituent in algorithmic decision-making.
- (p. 4)

Dogrue et al. (2022) provided a more concise definition, which is nearly as comprehensive the definition above. They identified four dimensions in algorithmic literacy and defined it as: “*being aware* of the use of algorithms in online applications, platforms, and services, *knowing* how algorithms work, being able to *critically evaluate* algorithmic decision-making as well as having the *skills to cope* with or even *influence* algorithmic operations [emphasis in original]” (p.4).

Other authors used shorter definitions, often focusing on one or two components. According to Cotter and Reisdorf (2020) algorithmic literacy “entail[s] familiarity with how algorithms work as well as the ability to assess their information outputs” (p. 759). Pethig and Kroenung (2022) used Cotter and Reisdorf’s work for their definition of algorithmic literacy: “the ability to understand and reflect on algorithmic decisions” (Practical Implications section, para. 2).

Reflection was also important for Lloyd (2019) and Dezuanni (2021). Lloyd (2019) mentioned how “reflexivity becomes an important aspect of information literacy, which can focus our attention on how algorithms are expressed and operationalised ..., along with the conditions, assumptions and biases that are inherent in their production and operationalisation” (p. 1483). Dezuanni (2021) stated that “[reflecting] critically on the role of algorithms in digital media culture has the potential to assist students to consider their level of agency over their own media choices” (p. 881).

Bakke (2020) also mentioned reflection as a necessary component, and added the necessity of awareness when teaching and promoting algorithmic literacy. This relates to Swart (2021), who defined algorithmic literacy as “the combination of users’ awareness, knowledge, imaginaries, and tactics around algorithms” (p. 2), and Kapsch (2022), who did not give a definition, but did underline that a first step for building algorithmic literacy was “making sense of and becoming more aware of the influence of algorithms in everyday life” (p. 5).

Shin et al. (2022) defined algorithmic literacy as “understanding what algorithms do and why, but also about what they mean” and described it as “a set of capabilities used to organise and apply algorithmic curation, control and active practices relevant when managing one’s AI environment” (p. 1217). In earlier work Shin (2021) explained that these practices were “social practices; the ways people use algorithms in their everyday lives and the events which are mediated by users’ interactions with actual algorithmic services” (p. 92).

Krippendorf (2019) wrote that algorithmic literacy was about examining “how algorithms are presented publically [sic] and what they do and for whom” (p. 87). He stated that the language used for algorithmic literacy should move away from describing computational technologies and move towards that of the “social consequence of their use” (p. 87), which should be done by adopting an interdisciplinary approach.

Associated concepts

Garingan and Pickard (2021) noted that multiple definitions and characteristics of algorithmic literacy existed in the literature, and did not give one single definition. More authors did not define algorithmic literacy further, even while using the term, such as Zarouali, Boerman, et al. (2021), Bastian et al. (2019), Helberger et al. (2020), and Brodsky et al. (2020). Likely they expected readers to understand what they meant based on the context of the article, even though there is clearly no consensus on what it exactly entails. Another interesting example is Bogina et al. (2022), who reported on giving a workshop on algorithmic literacy to school teachers, but without being clear how the authors exactly defined it. However, Bogina et al. mainly focused on fairness,

accountability, transparency, and ethics (FATE) in relation to algorithms, and this implied a relationship between algorithmic literacy and the four FATE concepts. This relationship could also be identified in other work (Krügel et al., 2022; Shin, 2021; Shin et al., 2022), and to transparency in particular (Helberger et al., 2020; Kiester & Turp, 2022; Krippendorff, 2019; S. Robinson et al., 2021; S. C. Robinson, 2020).

Trust is a concept related to fairness, accountability, transparency, and ethics, and has been studied by multiple authors as well. This was done in relation to trusting algorithmic decisions (Bakke, 2020; Krügel et al., 2022; Shin, 2021; Shin et al., 2022), but also to trusting institutions and mainstream media (Haider & Sundin, 2022b; S. C. Robinson, 2020).

Literacies landscape

The term algorithmic literacy was often placed in a combination of literacy traditions, including information literacy and digital literacy (Bakke, 2020; Cotter & Reisdorf, 2020; Ridley & Pawlick-Potts, 2021), media literacy and digital literacy (S. Robinson et al., 2021; Zarouali, Helberger, et al., 2021), information, media, and New Literacy (DeVito, 2021), information, digital, data, and computer literacy (Garingan & Pickard, 2021), and information, data, and technological literacy (Shin et al., 2022). In some cases the author(s) placed algorithmic literacy in a single tradition of literacy, mainly media literacy (Brodsky et al., 2020; Dezuanni, 2021; Swart, 2021), but also information literacy (Lloyd, 2019; O'Hara, 2021), digital literacy (Kapsch, 2022; Koenig, 2020), data literacy (Bastian et al., 2019; Kampa & Balzer, 2021), and mathematical literacy (Astambayeva et al., 2021). These results demonstrate that there are many different ideas about which literacy tradition algorithmic literacy belongs to, although the results indicate its place in both information literacy and media literacy. Its connection to digital literacy is also apparent, although this literacy tradition appeared broader, more diffuse, and less clearly defined, and was often related to other digital or technological literacies such as data literacy and computer literacy.

When reviewing the articles that did not use the term algorithmic literacy literally, many of these (combined) literacies were also found, although the scope was even broader. Besides information literacy (Gardner, 2019; Jiang & Vetter, 2020; Kiester & Turp, 2022; Svendsen et al., 2022), media literacy (Fouquaert & Mechant, 2021; Knaus, 2020; Valtonen et al., 2019), digital literacy (Bhatt & MacKenzie, 2019; Wiljer & Hakim, 2019), and digital literacies (de Roock, 2021; Jones, 2021; Marlatt & Sulzer, 2021; Yang, 2022), one could also encounter AI literacy (Eguchi et al., 2021), critical media literacy (Jiang & Vetter, 2020; Marlatt & Sulzer, 2021), critical literacy (Leander & Burriss, 2020), data literacy (Svendsen et al., 2022), critical data literacy (Claes & Philippette, 2020; Leicht-Deobald et al., 2019), statistical literacy (Claes & Philippette, 2020), computational literacy (Wiljer & Hakim, 2019), media and information literacy (Haider & Sundin, 2022a, 2022b), and technical literacies (Gallagher, 2020).

This raised the question of the usefulness of this multitude of terms for literacies. Ridley and Pawlick-Potts (2021) warned against using the term literacy too easily, and that using the term algorithmic literacy “must rest on a clear definition, a recognized problem and need, a pedagogical strategy, and a

unique (or at least supportive) contribution libraries can provide” (para. Introduction).

Nichols and LeBlanc (2021) took this discussion to a higher level, proposing to expand the idea of literacy and conceptualise the media environment as an ecological system, which algorithms are part of. The authors stated that this way of thinking could move some of the responsibility of dealing with the impact of algorithms away from users and onto the media system as a whole.

5.6 The necessity of algorithmic literacy

Many authors made calls to action to increase algorithmic literacy (e.g. Bakke, 2020; Bastian et al., 2019; Krippendorff, 2019; Krügel et al., 2022; Zarouali, Helberger, et al., 2021). But why might algorithmic literacy be necessary? Following the work of Haider and Sundin (2022c) on information literacy, the goals of algorithmic literacy are twofold. Raising the level of algorithmic literacy could benefit democracy (Bastian et al., 2019; König, 2022), fight inequality (Cotter & Reisdorf, 2020; Klawitter & Hargittai, 2018), and work towards closing the digital divide (Gran et al., 2021; Yang, 2022). Additionally, increasing people’s level of algorithmic literacy may lead to a more flexible and adaptable workforce in a capitalist society, where individuals need to have an adequate level of algorithmic literacy to be successful in their role as (prospective) workers (Smythe et al., 2021), and consumers (Helberger et al., 2020). These two goals sometimes overlap, which is especially clear in studies related to employment and entrepreneurship, as an adequate income for everyone is a necessity for creating a more equal society (Klawitter & Hargittai, 2018; Leicht-Deobald et al., 2019; Pethig & Kroenung, 2022; Smythe et al., 2021). Zarouali, Helberger, et al. (2021) stipulated that users needed algorithmic literacy to “be able to ask the necessary questions and hold controllers of algorithms accountable” (p. 135), which could be seen in both the democratic and capitalist view.

Multiple authors found a correlation between demographic and socioeconomic factors and the level of algorithmic literacy (Cotter & Reisdorf, 2020; Dogruel et al., 2022; Klawitter & Hargittai, 2018; Zarouali, Helberger, et al., 2021; this will be discussed further in Section 5.9), which indicates the potential positive impact of algorithmic literacy education on decreasing the digital divide. This also points towards the potential negative effect on groups of people and increasing the digital divide if they do not have sufficient levels of algorithmic literacy.

Algorithm bias

Regardless of the goal, algorithmic literacy has been proposed as a way of battling algorithm bias. Algorithm bias is the notion that there is bias in the output of algorithms. This occurs due to bias which exists in the algorithms’ code, and the data sets used to train algorithms. This has been illustrated by Noble (2018) in her work on how searches in Google for “black girls” repeatedly resulted in stereotypical images, thus replicating and enforcing bias. By increasing algorithmic literacy and learning how bias might occur in algorithmic platforms or services, users should be able to cope with this phenomenon better (Bogina et al., 2022; de Roock, 2021; Gardner, 2019; König, 2022; Lloyd, 2019; O’Hara, 2021; Pethig & Kroenung, 2022; Trammell

& Cullen, 2021; Yang, 2022). König (2022) pointed out how users should examine their own values and beliefs, and be aware of their own biases, to be able to understand, work with and control algorithmic platforms.

Krügel et al. (2022) found that people tended to trust ethical advice on decision-making from an algorithm regardless what they knew of its workings or training data, and any potential bias. In a wider context of bias, Pethig and Kroenung (2022) studied the relationship between gender and the perceived bias of humans versus algorithms. They pointed out that people tended to perceive algorithms as neutral, objective, and sometimes better suited to make decisions than humans. They found this was especially true for women who were seeking work, and preferred their CVs to be judged by algorithms rather than by men. This is problematic, as this would mean that women are more likely to unknowingly subject themselves to algorithm bias.

5.7 Algorithm awareness as the basis for algorithmic literacy

Algorithm awareness, in other words being aware that algorithms play a role in digital information encounters, was frequently named as forming the basis for algorithmic literacy (Bakke, 2020; Bogina et al., 2022; Dogruel et al., 2022; Shin et al., 2022; Swart, 2021). In some cases algorithm awareness and the connection to algorithmic literacy was a central concept in a study: as a means of increasing algorithmic literacy among students (Brodsky et al., 2020), or as a conceptual basis to measure algorithmic literacy (Dogruel et al., 2022). In other cases the relationship between awareness and literacy was found later, which was the case in the work of Kapsch (2022), who studied a group of students reflecting on algorithms. He witnessed them become more aware of algorithms, and concluded the interventions he had used could be suitable for building algorithmic literacy. Similar concepts were algorithmic knowledge and algorithmic skills. Cotter and Reisdorf (2020) named algorithm awareness as a component of algorithmic knowledge, and Klawitter and Hargittai (2018) did the same for algorithm awareness and algorithmic skills. Interestingly, these studies also have in common that the connection with algorithmic literacy was only established later, meaning that these studies did not intend to make a contribution to algorithmic literacy research, although this was in fact a result. This adds to the notion of algorithmic literacy as an emerging topic.

While some authors mentioned algorithm awareness without further elaboration, others dedicated part or much of their work to differentiating between levels of awareness. Koenig (2020) distinguished between three levels of awareness: basic, critical, and rhetorical. This was based on the work of Selber (2004) on technological multiliteracies, who used the terms functional, critical, and rhetorical literacy. Garingan and Pickard (2021) built further on Selber's and Koenig's work by applying it to algorithmic literacy. Zarouali, Boerman, et al. (2021) discerned five dimensions of awareness: (1) of content filtering; (2) of automated decision-making; (3) of human-algorithm interplay; (4) of algorithmic persuasion; and (5) of ethical considerations (para. 2.2 Dimensions of algorithmic awareness).

DeVito (2021) studied groups of users which already had some level of awareness, in this case due to their queer identities and self-presentation needs.

She mentioned the need to also study users that were pre-aware and users with basic awareness in order to establish what interventions would work for them.

5.8 Teaching and learning algorithmic literacy

Teaching and learning algorithmic literacy was a topic for many studies. Both the evaluative and the explorative approaches could be encountered in these studies. On the one hand studies following the evaluative approach of studying information literacy could be identified, where formal teaching or learning environments are of interest. This included its place in curricula, what methods and interventions were chosen, and who was responsible for teaching – librarians or other teachers. On the other hand the explorative approach was encountered in studies that focused on practices and experiences of users and how these influenced their level of algorithmic literacy.

The role of librarians

Not surprisingly, the five articles written by librarians all focused on the role of librarians in teaching algorithmic literacy. Two articles focused on specific academic and professional groups of librarians and information users. Garingan and Pickard (2021) examined the roles of the legal librarian, and Kiester and Turp (2022) investigated the roles of the medical librarian. Two articles focused more generally on the academic librarian (Gardner, 2019; O’Hara, 2021) and one on the public librarian (Ridley & Pawlick-Potts, 2021).

Garingan and Pickard (2021) examined the roles of the legal librarian, both in an academic and in a legal practice setting. They underlined that legal librarians should both have a high level of algorithmic literacy themselves, and play an active role in algorithmic literacy instruction for legal professionals. They explored different frameworks and concepts to this end. From librarianship, the ACRL framework (Association of College & Research Libraries, 2016) and the Seven Pillars of Information Literacy (SCONUL, 2011) were named, as was the work by Koenig (2020). Garingan and Pickard (2021) also examined options from a more technological viewpoint, by including Selber’s (2004) Three Categories of Computer Literacy, and by explicitly linking the notion of explainable AI to algorithmic literacy by including work of Turner (2019) on evaluating AI systems. While Garingan and Pickard (2021) showed how these frameworks and concepts might be adapted for algorithmic literacy, they also concluded that a new literacy framework could be developed, as long as it was aimed at developing higher levels of algorithmic literacy, which they thought necessary for legal information professionals. They declared that identification, explanation, bias and limitations of use needed to be a part of any algorithmic literacy framework.

Ridley and Pawlick-Potts (2021) wrote about the role of public libraries, drawing similar conclusions to Garingan and Pickard (2021), even though these libraries target a much wider audience: learning algorithmic literacy was both for the benefit of librarians and of the public. They stated how libraries could start partnerships with schools and other educational initiatives, and made a strong case for the potential role of libraries in education and assessment. Furthermore, like Garingan and Pickard, they noted how libraries

could incorporate explainable AI in their work towards advancing algorithmic literacy.

O'Hara (2021) focused on the role of the academic librarian and how they could incorporate algorithmic literacy in information literacy instruction for students. He proposed to use the ACRL framework to build information literacy instruction on, especially focusing on the frames *Authority is constructed and contextual* and *Information has value*. Librarians could instigate discussions based on activities, for example by asking students to individually search for a certain topic, and then critically discuss the results in the context of authority, and political and financial value. He recognised the potential problem of the “typical one-shot instruction model” (p. 12) of information literacy instruction and proposed how to organise these activities and discussions on a smaller scale.

Gardner (2019) also used the ACRL framework to design and teach a university course on information literacy which focused on algorithm bias. Besides the frames *Authority is constructed and contextual* and *Information has value*, she included the frames *Scholarship as conversation*, and *Information creation is a process*. In this course students were challenged to consider how some sources had more privilege in a search system over others, how search systems did not show “a natural reflection of the world” in their results (p. 326), what the algorithm's role was in personalised results, and the fact that most search engines were funded by advertising.

Kiester and Turp (2022), taking a different path, did not propose to use any frameworks, but rather focused on ethical implications of a new ranking algorithm in the medical database PubMed. They proposed that librarians should play a role in teaching professional health information users about how algorithms function in this database, with a focus on transparency and accountability.

The role of schools and curricula

Some authors discussed the role of teachers and literacy education rather than the role of librarians. Yang (2022) focused on algorithmic literacy education for young children and places it in the STEAM (Science, Technology, Engineering, Arts, Mathematics) curriculum. He noted how algorithmic literacy education should be “embodied and culturally responsive” (p. 3), meaning that learning experiences should be adjusted to the learner's social and cultural reality and connect the body, the mind and real life. The learning goals should focus on four outcomes: recognising algorithms, having a basic understanding how they are trained, having an understanding of bias, and knowing that algorithms can make mistakes. Eguchi et al. (2021), writing about AI education for primary and secondary schools, also specifically noted that education should be culturally responsive. They presented a project for Japanese schools, focusing on examples that are relevant for children growing up in Japan.

Dezuanni (2021) scrutinised the Australian media literacy education curriculum and gave recommendations based on changes in digital media over the last ten years, including the impact of algorithmic culture, which can be described as the role of algorithms in (digital) culture, on user's agency. He did

not propose any concrete interventions but rather stipulated the importance of algorithmic literacy, urging educators, schools and authorities to become involved in this subject, and not to refuse it for being too difficult.

How to learn algorithmic literacy

Independent of the question by whom and where in the curriculum algorithmic literacy might be taught, the question of how algorithmic literacy can be learned is also central in many authors' work. The work of Zarouali, Helberger, et al. (2021) joined formal and informal learning, as they found that users appeared to have a higher level algorithmic literacy thanks to personal experiences with algorithms, information in the media, and formal education. However, Swart (2021) found that the role of formal (media) education was smaller compared to that of informal learning, except for specific ICT skills such as coding. Zarouali, Helberger, et al. (2021) found that the level of algorithmic literacy was lower if people only relied on information from family and friends, or had no information source at all. Cotter and Reisdorf (2020) concluded that high frequency and breadth of use of search engines had a positive correlation with the level of algorithmic knowledge.

According to Swart (2021), young people mainly learned about algorithms through personal experiences, including expectancy violations. They had their own imaginaries about how algorithms work, and learned about their functioning when they did not work as expected. This confirmed DeVito's (2021) work, who used the concept of folk theories when discussing how people imagined complex things, such as algorithms, to operate. Expectations were also central to the work of Haider and Sundin (2022a), who introduced the idea that young people anticipated a certain outcome when using algorithmic systems. They studied the notion of anticipation as a way of understanding how people imagined algorithm platforms to work, how to engage with algorithms, and how they learned about them.

Besides studying what processes and factors play a role in learning algorithmic literacy, a number of authors presented formal interventions to increase algorithmic literacy. These could be very simple, such as a video explaining algorithms (Brodsky et al., 2020), or more complex, like a tool aimed at visualising Instagram's curation algorithm (Fouquaert & Mechant, 2021). Multiple interventions involved development of critical thinking about algorithms, often through discussions and reflection exercises (Bakke, 2020; Kapsch, 2022; Koenig, 2020). As Jones (2021) noted, engaging students in critically examining their interactions with algorithms by challenging them to imagine how they might work may be a good basis to building algorithmic literacy. Jiang and Vetter (2020) suggested that rhetorically analysing algorithmic interactions on Wikipedia could also be useful as an intervention.

Koenig (2020) proposed journal writing exercises to build awareness further: by reflecting on the interactions with algorithms, students moved from basic awareness to higher levels of critical and rhetorical awareness. Kapsch (2022) introduced reflection exercises through the making of vlogs, in which students reflected on what was happening, what the algorithms were doing, what they themselves were doing to influence the outcome, and lastly to reflect on what they had learned about algorithms through the exercises.

Authors who studied users' imaginaries or folk theories, implicitly or explicitly assumed that technological, mathematical, and statistical knowledge about algorithms was not required to build algorithmic literacy. However, other authors stipulated that this kind of knowledge was in fact necessary. Valtonen et al. (2019) and Vartiainen et al. (2020) wrote about how knowledge about machine learning was an essential part of algorithmic literacy, and Astambayeva et al. (2021) focused on including the mathematical principles of algorithms when teaching algorithmic literacy.

Gallagher (2020) made a case that working with algorithms in an ethical way required a solid understanding of basic algorithmic concepts, even for non-technical or mathematical users. He came to this conclusion after having designed and taught a course for undergraduate and graduate students about algorithms in the context of communication studies. He noted that while the students were capable of noticing expressions of algorithms, they were not able to assess the actual workings of the algorithms. This was either due to unclear or incomplete information or documentation, or due to lacking technical and statistical knowledge. Wiljer and Hakim (2019) drew similar conclusions for health care professionals. They mentioned that statistical knowledge should be increased, as well as the knowledge about the role of data in algorithmic applications for healthcare, with a special focus on potential implications of using algorithms in clinical practice.

5.9 Studying algorithmic literacy

Different authors have taken various approaches in studying algorithmic literacy. Many of the studies into measuring algorithmic literacy were of quantitative nature. This fits the evaluative approach of algorithmic literacy research, where norms are important and consequently measuring is as well. Additionally, the explorative approach can be found in the qualitative studies writing about experiences, practices, and attitudes (e.g. Haider & Sundin, 2022b; Hargittai et al., 2020; Swart, 2021).

An interesting perception with regard to studying algorithmic literacy came from Swart (2021), who pointed out that if a user did not know the right vocabulary to talk or reason about algorithms, it did not necessarily mean that they had a low level of algorithmic literacy. In her study, the young participants she interviewed could generally describe in detail how they thought algorithms functioned, but without using the algorithmic terms. This indicated they had some level of algorithmic literacy, but might lack the vocabulary to describe the processes involved when using algorithmic services. This clearly has implications for both evaluative and explorative studies, and the choice researchers make about the vocabulary to use in their research methods, such as surveys and interviews.

Level of algorithmic literacy

Multiple authors attempted to measure algorithmic literacy or its components in some way. This will be discussed in more depth in the next paragraph on measuring algorithmic literacy. Other authors made assumptions based on the digital skills of their subjects (DeVito, 2021), or previous research (Kapsch, 2022, who referred to Gran et al. (2021)). However, given the diverse nature of methods, which often used unvalidated measurements, and the variation in

sizes of groups studied, the results were often merely anecdotal and could hardly be compared. For example, it appeared that medical students had low levels of algorithmic literacy because of low scores in a knowledge test (Kampa & Balzer, 2021), while creative entrepreneurs had high scores on a skills test (Klawitter & Hargittai, 2018). However, it is more likely that the level of algorithmic literacy in the general public is on the low side. This follows the findings of Gran et al. (2021), who found that over half of the Norwegian population had little to no awareness of algorithms, even though Norway is a highly educated and digitalised country. Zarouali, Helberger, et al. (2021) drew similar conclusions for the Dutch population.

Nonetheless, some demographic and socioeconomic factors were identified that influenced the level of algorithmic literacy. Multiple authors found a positive correlation between algorithmic literacy, lower age, and higher education (Cotter & Reisdorf, 2020; Dogruel et al., 2022; Zarouali, Helberger, et al., 2021). Additionally, Cotter and Reisdorf (2020) found a positive correlation with higher income. They also investigated the relationship between gender, ethnic origin, and algorithmic literacy, but they did not find one. Zarouali, Helberger, et al. (2021) also examined the role of gender, and found that men had a higher level of literacy than women. Dogruel et al. (2022) also found that men scored slightly higher than women, but they did not present this finding as a conclusion. Although it was significant, the difference was small. No other authors studied a possible relationship between algorithmic literacy and ethnicity.

Measuring algorithmic literacy

Hargittai et al. (2020) found three components that were relevant when studying users' level of algorithmic literacy: awareness, understanding, and attitudes. This is a useful distinction to classify the studies concerned with determining the level of (components of) algorithmic literacy. Several studies focused on measuring awareness (Brodsky et al., 2020; Fouquaert & Mechant, 2021; Gran et al., 2021; Helberger et al., 2020; Zarouali, Boerman, et al., 2021). Other studies focused on knowledge or skills (Cotter & Reisdorf, 2020; Kampa & Balzer, 2021; Klawitter & Hargittai, 2018), which could be seen as the understanding component of Hargittai et al. (2020). Furthermore, a number of studies examined users' attitudes towards algorithms (Gran et al., 2021; Haider & Sundin, 2022b; Hargittai et al., 2020; Kampa & Balzer, 2021; Swart, 2021). Although these studies did not measure algorithmic literacy directly, the potential use of the study in the context of measuring algorithmic literacy was sometimes mentioned explicitly (Dogruel et al., 2022; Zarouali, Boerman, et al., 2021).

Multiple authors studied awareness and understanding in the form of knowledge or skills, or a combination thereof. Quantitative studies often attempted to measure this in some way, although parameters and algorithmic systems varied. Zarouali, Boerman, et al. (2021) noted that previous attempts at measuring algorithmic awareness or knowledge often worked with questions that were only relevant in the context of that specific study, thus being neither a reliable, nor consistent method for measuring and comparing algorithmic awareness. The lack of validated scales made it difficult to standardise measurement and extrapolate results. Consequently, two studies focused on developing a validated instrument (Dogruel et al., 2022; Zarouali, Boerman, et

al., 2021), although neither appear to have been adopted yet by other researchers. Many studies reported using questions related to real-life situations (Brodsky et al., 2020; Cotter & Reisdorf, 2020; Dogruel et al., 2022), taking into account Swart's (2021) notion about users potentially not knowing algorithmic vocabulary.

Validated scales

As mentioned, two validated scales have been developed: one by Zarouali, Boerman, et al. (2021) and one by Dogruel et al. (2022). Zarouali, Boerman, et al. (2021) measured algorithmic awareness and developed and validated the Algorithmic Media Content Awareness scale (AMCA-scale). Although they stipulated that the exact relationship between algorithmic awareness and algorithmic literacy needed to be studied further, they wrote that the scale might be used to measure the "overall 'algorithmic literacy' of a given population" (para. 4.1 Theoretical implications). The level of algorithmic awareness was measured by presenting users with true/false statements about common misconceptions regarding algorithms and their use. The notion of studying misconceptions as an indicator for measuring algorithmic literacy followed from previous work by Zarouali, Helberger, et al. (2021). This study was partially done by the same authors. The user's awareness was measured by presenting 13 items, based on four dimensions of awareness. These four dimensions focused on content filtering, automated decision-making, the interplay between humans and algorithms, and ethical issues. Notably, the authors did presume the participants in the study to know vocabulary related to algorithms.

As Dogruel et al. (2022) pointed out, the AMCA-scale only focused on one type of algorithmic system users might encounter, namely algorithmic content recommendations in social media and streaming services. This might make the scale less appropriate to study algorithmic literacy for other algorithmic systems. Dogruel et al. (2022) aimed to close this gap with their validated scale examining users' algorithmic knowledge and awareness, which they identify as key components of algorithmic literacy. They took into account that users may not have the right vocabulary to reason about algorithms, as Swart (2021) found, by asking about experiences with concrete examples of algorithmic systems rather than directly asking users about their level of awareness on algorithms in certain functionalities, in contrast to what Zarouali, Boerman, et al. (2021) did.

Attitudes and agency

In their study interviewing adults from several countries in Europe and the USA, Hargittai et al. (2020) found positive, neutral, and negative attitudes towards algorithms. Participants disclosed their views both in direct questions about attitudes, and as comments to other questions. While attitudes were not the main focus of this study, the authors noted the potential connection of attitude on one side, and awareness and understanding on the other, pointing it out as a topic for future research.

Swart (2021) had similar findings in her study of Dutch young people, where participants mentioned having positive, neutral, or negative emotions towards algorithms.

Gran et al. (2021) statistically proved the correlation between awareness and attitude. They identified six clusters of users: unaware, uncertain, affirmative, neutral, sceptic and critical. Users labelled unaware and uncertain had no or low awareness of algorithms, and mainly held neutral attitudes towards the algorithms they were aware of. Affirmative users were characterised by a positive attitude and being somewhat aware. Neutral users also had some level of awareness, but were more neutral towards algorithms compared to affirmative users. Sceptical users tended to have low to medium level of awareness, with neutral to negative attitudes. Critical users had the highest level of awareness, and held mainly negative attitudes towards algorithms.

Haider and Sundin (2022b) – although their work focused on agency and trust – found similar user types as Gran et al. (2021): the non-evaluator, the naïve evaluator, the confident evaluator, and the sceptical evaluator. This gives the impression that awareness, understanding, and attitude may be related to agency and trust, although this should be examined further.

Claes and Philippette (2020), Kapsch (2022), and König (2022) also connected agency with algorithmic literacy. König (2022) focused specifically on how users could engage deliberately with algorithms to change outcomes, and how this could raise awareness and understanding in the sense of critical thinking and reflecting on one's own use of media. Similarly, Claes and Philippette (2020) wrote about the necessity of algorithmic literacy initiatives to “stimulate learners' willingness to engage critically with richer interfaces to consciously manage their media ecosystem” (p. 25). König (2022) connected agency with control, describing how users should not only have knowledge about algorithmic systems, but also about their own personal needs and beliefs. To be able to exercise their agency and have control over algorithmic systems, users would need insight into both, in order to adequately decide what parameters in algorithmic systems would line up most closely to their personal values. They would also need to examine their personal biases closely. According to the author, gaining control and building algorithmic literacy was necessary to exercise agency and counter the potentially biased, negative outcomes of algorithms in society.

6 Discussion and conclusion

This thesis aims to answer research questions related to the concept of algorithmic literacy, its place in the literacies landscape, terminology used, how it is being studied, what is known based on these studies, and what knowledge gaps exist. These research questions fulfil the scoping review's goals of summarising and disseminating the current state of knowledge about algorithmic literacy, as well as the goal to make suggestions for further research based on the identified knowledge gaps. In the following sections the research questions are answered and future research suggestions are given.

6.1 Algorithmic literacy as a concept

The first research question asks: What is known about the concept of algorithmic literacy, how is it related to information literacy and other related literacies, and what terms are being used to describe algorithmic literacy and related topics?

It has become clear that algorithmic literacy cannot be defined in one single way, although awareness, understanding (which might consist of knowledge and/or skills), and reflection are important components. It is often placed in one or multiple literacies: information literacy, media literacy, and digital literacy/literacies appear frequently in the research. This landscape becomes even more diverse when the term algorithmic literacy is not used literally. While authors might have good reasons to use different terminology, it is obvious that this is not beneficial for conceptualising and studying algorithmic literacy. However, it is not uncommon in the field of information literacy research that many different terms are in use. Hence, it is unlikely that a single term or a single definition will be used by everyone. Nonetheless, it would be beneficial for the research community to try to limit the number of terms used, and to always clearly define what is meant with a specific term.

Multiple terms that are closely related to algorithmic literacy have been identified, and these sometimes appear to be used as synonyms. This includes AI literacy, algorithm awareness, algorithmic knowledge, and algorithmic skills. Algorithm awareness can be seen as the basis for algorithmic literacy, and together with algorithmic knowledge and algorithmic skills, these can be seen as components of algorithmic literacy. These three concepts are also often objects of measurement. The multiple components of algorithmic literacy can be seen as a further reason why its conceptualisation is complex, and the relationships between these components should be studied further.

Furthermore, other concepts have been identified that likely play a role in algorithmic literacy, most notably attitudes, agency, trust, and transparency. These concepts are mostly found through the explorative approach of research, where experiences and practices are being studied. Further exploration may yield more concepts, and further research into the interrelatedness of these concepts should also be undertaken.

6.2 The study of algorithmic literacy

The second research questions asks: How is algorithmic literacy being studied, and what do we know about algorithmic literacy from these studies?

When answering the first part of this question, how algorithmic literacy is being studied, it becomes clear that both empirical research and theoretical articles have a place in the study of algorithmic literacy. Around half of the empirical studies included in this review employed quantitative methods. Many of these studies undertook research into measuring the level of algorithmic literacy, awareness, or knowledge. This corresponds with the evaluative approach of information literacy research (Lundh et al., 2013), as described in Section 2.2, where there is a strong normative component. Two validated scales have been identified: the Algorithmic Media Content Awareness scale (AMCA-scale) (Zarouali, Boerman, et al., 2021), and the algorithmic literacy scale by Dogruel et al. (2022). Many of the empirical studies using qualitative methods can be seen as applying the explorative approach of information literacy research (Lundh et al., 2013), which was also described in Section 2.2. The experiences and practices of information users were being studied in the context of algorithmic literacy in order to describe how algorithmic literacy is built and experienced, and what variations might exist between different people and different groups. Many of these studies focused on user groups who were very active users of algorithmic services, especially young people and students. Two studies qualitatively explored documents to gain a better understanding of the role of algorithmic literacy in policy and practice.

Both the evaluative and the explorative approaches of research, which have often been used for information literacy studies (Lundh et al., 2013), thus appear also relevant and useful when studying algorithmic literacy, and result in a well-rounded view of algorithmic literacy. The explorative approach reveals the intricacies of the subject. By studying the experiences of different user groups insights may be gained how people learn algorithmic literacy, what experiences are common for many people, and what experiences are specific to certain groups. This gives the opportunity to identify specific types of users, which can be useful for further research and may result in new ways of studying algorithmic literacy. The evaluative approach provides the opportunity for advancing measurement and education on this topic. A well-defined, validated measurement method can be helpful in certain contexts, such as to identify gaps in users' knowledge, or for gaining insight into the usefulness of certain interventions aimed at increasing algorithmic literacy.

The second part of the research question, what we know about algorithmic literacy from these studies, can be answered as followed. The conclusion can be drawn that demographic and socioeconomic factors play a role in levels of algorithmic literacy. It appears that younger people have a higher level than older people, and people with a higher education have a higher level than people with a lower education. Additionally, it might be the case that men have a higher level than women, although there is no consensus on the role of gender. Consequently, it seems that groups that are often disadvantaged due to other global and technological developments overlap with the groups of people that are negatively impacted by algorithmic services. This underlines the importance of building algorithmic literacy in these groups especially, and also

the necessity of studying other commonly disadvantaged groups, such as people from the global South, from rural areas, and from lower income families.

Furthermore, people's attitudes towards algorithms appear to play a role in their level of algorithmic literacy, especially in combination with awareness. Having a negative attitude towards algorithms can in some cases be associated with a higher level of algorithmic literacy. It is likely that this is also linked to critical thinking skills, thus studying ways to foster critical thinking in relation to algorithmic literacy can be insightful. Interestingly, the studies in this review which focused on attitudes were both of quantitative and of qualitative nature, and approached this topic exploratively rather than evaluatively. This could indicate that there is no single, 'correct' attitude for higher levels of algorithmic literacy, although variations in attitude, in connection with critical thinking and algorithm awareness, likely play a role.

A higher level of algorithmic literacy can be achieved through personal experiences and via formal education. Expectancy violations play a role in these personal learning experiences. In formal education algorithmic literacy can be part of information literacy, media literacy, or another part of the curriculum. No stark differences or clear advantages were found to claim that algorithmic literacy education should be placed in a specific literacy curriculum. However, it has become clear that algorithmic literacy should be a part of education from a young age up until university and even continuing during people's professional lives. While it is possible that this is undertaken in a single event, it is likely that complete courses aimed at improving algorithmic literacy have better results, although this would require more time and highly educated staff. Librarians or other teachers with enough knowledge on this subject can design and organise these events or courses, given that curriculum directors allow for enough time for designing and teaching. Many different interventions have already been proposed, and those with a reflexive component appear particularly useful. It would be beneficial for educators if the materials used were shared, thus benefiting multiple teaching communities. Given the usefulness of culturally and socially relevant materials, it would make sense if these communities were organised on a regional or national level. There is some discussion on whether technological, mathematical and/or statistical knowledge is required in algorithmic literacy education. It likely depends on the educational context what is appropriate and useful. Future research into this topic is needed as well.

6.3 Identified knowledge gaps

Based on the articles included in this scoping review, a number of topics could be identified as knowledge gaps, and could provide an agenda for further research topics. These topics seem particularly interesting as they have not been researched enough – or at all – and appear highly relevant in the presented context.

Further development and use of validated scales

Further research is needed to explore if is the AMCA-scale, which measures algorithm awareness and predicts algorithmic knowledge, also predicts algorithmic literacy. Additionally, more studies into both validated scales

would be useful, especially longitudinal studies and studies in different cultural contexts. Furthermore, it is possible that other studies exist which focus on measuring algorithm awareness and/or algorithmic knowledge, but without an explicit connection to information literacy or algorithmic literacy. Reviewing whether these exist could give further advancement to developing methods for measuring algorithmic literacy as well.

Negative attitude

A negative attitude towards algorithms correlates in some cases with higher algorithmic literacy. Future research could explore what components of this negative attitude play a role. This could also foster future interventions in order to encourage a critical stance towards algorithms. A specific group of users that might be of interest in this context are those who have experience with algorithmic systems but have chosen to stop using them, such as people who have left social media.

Agency and trust

The relationship between agency, trust, and algorithmic literacy may be studied further. Haider and Sundin (2022b), who focus on agency and trust, find similar user types as Gran et al. (2021), who study awareness, understanding, and attitude. Agency may correspond with awareness and understanding, which is needed to work with and influence algorithmic systems, and trust may correspond with understanding and attitude. The non-evaluator (low trust, low agency) is likely to have low awareness and corresponds with the uncertain user. The naïve evaluator (high trust, low agency) may have low to some awareness and corresponds with some of the neutral and affirmative users. The sceptical evaluator (low trust, high agency) likely has medium to high awareness and a negative attitude, thus corresponding with the critical user. The confident evaluator (high trust, high agency) likely has medium to high awareness and a neutral to positive attitude, corresponding partly with the affirmative and neutral users. This gives the impression that awareness, understanding, and attitude may be related to agency and trust, and should be examined further. This could result in more well-defined descriptions and typologies of users, which could be helpful for gaining insight in the experiences of specific user types, and may also be helpful for creating more effective interventions aimed at these users.

Algorithmic literacy and alt-right media

Increasing democracy is often mentioned as a goal of algorithmic literacy education. In the current information landscape, however, it appears that anti-democratic messages are also advanced through increased algorithmic literacy of users and makers of alt-right media (Haider & Sundin, 2022c). No studies have been identified into algorithmic literacy practices or skills in this context, thus further research is needed, both from the users' and the producers' perspective. Knowing how information users encounter this kind of information and what can be done to counter their potentially negative effects, such as believing misinformation and spreading it further, would be meaningful. Additionally, having more insight in how alt-right media producers build their algorithmic literacy with their goal of spreading their messages could bring opportunities to battle this. It might also give ideas on how to advance algorithmic literacy in the general public.

Larger variety of users and other subjects

The studies focus mostly on North America and Europe, leaving South America, Africa, and Asia underrepresented. Further studies should aim to include these areas, especially given the potentially growing digital divide and inequality of marginalised communities. Further research should also include the groups identified in this review as having lower algorithmic literacy: women, older people, people with lower education, and people with lower income. It is likely that more demographic and socioeconomic factors play a role in the level of algorithmic literacy, therefore extra attention should be given to identifying those factors and studying these groups as well. Special interest should also be given to users with no or low algorithm awareness.

Additionally, little empirical research has been done with children as subjects. Further research on children's practices would benefit the field, as would extending research into interventions and methods to measure algorithmic literacy in this group.

Furthermore, more research into policy documents, comparing different countries, regions, or changes over time, is likely to be insightful, especially if this can be connected to the results of interventions and education. Other documents may also be interesting subjects, such as documents describing how certain algorithms work, and how users make sense of this information. This would also benefit research into explainable AI.

Algorithms in professional settings

More research is needed into algorithmic literacy in professional settings. This is especially true for people working with automatic decision-making algorithms, as the impact of these decisions can be far-reaching. This was also shown by O'Neil (2016) in the context of legal and other public professions. From this review, the conclusion can be drawn that health care professionals need to increase their level of algorithmic literacy (Kampa & Balzer, 2021; Wiljer & Hakim, 2019), as do HR professionals (Leicht-Deobald et al., 2019), and creative entrepreneurs (Klawitter & Hargittai, 2018). Nonetheless, these studies only represent a relatively small amount of studies in this review. Therefore, it is necessary that further research is undertaken, both using the evaluative approach by focusing on measuring and teaching algorithmic literacy, and the explorative approach, aiming to bring to light how certain professional groups experience and practice algorithmic literacy.

7 Recommendations for further research

In addition to the recommendations and topics presented in Chapter 6 as suggestions for future research, further recommendations can be made based on the limitations mentioned in Section 1.3. These include recommendations for choice of terms in the query, databases used, and limitations for the documents included in the review.

As noted in Section 6.1, multiple closely related terms have been identified that appear to be used as synonyms as well. Also, it is possible that researchers from other disciplinary backgrounds use different terminology than algorithms or literacy, but are in fact discussing similar matters as those who do. This could be the case for researchers who prefer the terms AI or artificial intelligence to algorithms, or those who write about education, knowledge or skills, but not literacy. In future research, especially if building upon or extending this review, it could be useful to include some or all of these terms.

Different databases could be included to broaden the coverage of indexed articles. Especially adding another broad multidisciplinary database, such as Web of Science, could potentially increase the number of relevant articles and broaden the scope. This would be specifically applicable if the aim was to retrieve as many as possible articles on this topic, for example when choosing a different documentary research method, such as the systematic review. Furthermore, other types of texts besides academic articles could be included, such as conference papers and trade magazines or other grey literature. Also, texts in other languages than English could be considered to broaden the scope. Finally, a larger time frame could be chosen to gain a better understanding of historical developments.

However, any of these changes would most certainly result in an increased amount of documents to inspect and to include in the review. This would mean a larger time investment, although working in a team and dividing the work may decrease the throughput time of the study. Additionally, by undertaking a scoping review as a team, accuracy may be improved and bias might be reduced. Furthermore, other review methods could also broaden the picture and deepen our understanding of algorithmic literacy. For example, a systematic review of specific interventions could be undertaken and improve algorithmic literacy education, and policy research could further investigate current policies and be beneficial for future policy-making.

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Appendix A – Overview of the articles included in the scoping review

<i>Author(s), year,</i>	<i>Article type</i>	<i>Type of research (if research article)</i>
Astambayeva et al., 2021 *)	Research article	Quantitative
Bakke, 2020 *)	Research article	Qualitative
Bastian et al., 2019 *)	Theoretical paper	n/a
Bhatt & MacKenzie, 2019	Research article	Qualitative
Bogina et al., 2021 *)	Research article	Mixed methods
Brodsky et al., 2020 *)	Research article	Quantitative
Claes & Philippette, 2020	Theoretical paper	n/a
Cohen, 2018	Essay	n/a
Cotter & Reisdorf, 2020 *)	Research article	Quantitative
de Roock, 2021	Theoretical paper	n/a
DeVito, 2021 *)	Research article	Qualitative
Dezuanni, 2021 *)	Theoretical paper	n/a
Dogrueel et al., 2022 *)	Research article	Quantitative
Eguchi et al., 2021	Project report	n/a
Fouquaert & Mechant, 2021	Research article	Quantitative
Gallagher, 2020	Research article	Qualitative
Gardner, 2019	Column	n/a
Garingan & Pickard, 2021 *)	Theoretical paper	n/a
Gran et al., 2021 *)	Research article	Quantitative
Haider & Sundin, 2022a	Research article	Qualitative
Haider & Sundin, 2022b	Research article	Qualitative
Hargittai et al., 2020	Research article	Qualitative
Helberger et al., 2020 *)	Theoretical paper	n/a
Jiang & Vetter, 2020	Research article	Qualitative
Jones, 2021	Research article	Qualitative
Kampa & Balzer, 2021 *)	Research article	Quantitative
Kapsch, 2022 *)	Research article	Qualitative
Kiester & Turp, 2022	Knowledge synthesis	n/a
Klawitter & Hargittai, 2018 *)	Research article	Qualitative
Knaus, 2020	Theoretical paper	n/a
Koenig, 2020 *)	Research article	Qualitative
König, 2022 *)	Theoretical paper	n/a
Krippendorff, 2019 *)	Essay	n/a
Krügel et al., 2022	Research article	Quantitative
Ku et al., 2019	Research article	Quantitative
Leander & Burriss, 2020	Theoretical paper	n/a
Leicht-Deobald et al., 2019	Theoretical paper	n/a
Lloyd, 2019 *)	Theoretical paper	n/a
Marlatt & Sulzer, 2021	Research article	Qualitative

Nichols & LeBlanc, 2021	Theoretical paper	n/a
O'Hara, 2021 *)	Theoretical paper	n/a
Pethig & Kroenung, 2022 *)	Research article	Quantitative
Ridley & Pawlick-Potts, 2021 *)	Theoretical paper	n/a
S. C. Robinson, 2020	Research article	Mixed methods
S. Robinson et al., 2021 *)	Research article	Qualitative
Shin et al., 2022 *)	Research article	Quantitative
Shin, 2021 *)	Research article	Quantitative
Smythe et al., 2021	Research article	Mixed methods
Svendsen et al., 2022	Research article	Qualitative
Swart, 2021 *)	Research article	Qualitative
Trammell & Cullen, 2021 *)	Research article	Qualitative
Valtonen et al., 2019	Theoretical paper	n/a
Vartiainen et al., 2020	Theoretical paper	n/a
Wiljer & Hakim, 2019	Commentary	n/a
Yang, 2022	Project report	n/a
Zarouali, Boerman, et al., 2021 *)	Research article	Quantitative
Zarouali, Helberger, et al., 2021 *)	Research article	Quantitative

*) article contains *algorithmic literacy* as a term