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DISCUSSION

Algorithmic Literacy: A Compass to Successfully Navigate the Algorithm-Driven World?

Irina Heimbach · Olga Abramova · Annika Baumann · Hanna Krasnova · Ekaterina Jussupow · Christine Legner · Antonia Meythaler · Oliver Müller · Marc Pinski

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1 Introduction

1.1 Motivation

Determined by algorithms, i.e., a set of rules to be followed in calculations, computers have altered how we tackle and organize various activities across many domains. Initially applied to simple tasks premised on human control, today's algorithmic advances have taken over management (Möhlmann et al. 2021) and mimic human intelligence processes (Benbya et al. 2024). Since algorithms permeate nearly every sphere of human life, the public must be equipped with the necessary tools, skills, and knowledge to use them comfortably, innovatively, responsibly, effectively, and ethically.

Indeed, new algorithmic tools are continually emerging on the market. Their user-friendly interfaces offer a low entry barrier for professionals and the broader public. The

I. Heimbach (✉)
Weizenbaum Institute for the Networked Society,
Hardenberstrasse 32, 10623 Berlin, Germany
e-mail: irina.heimbach@outlook.de

O. Abramova
Institute of Information Systems, Leuphana University of
Lüneburg, Universitätsallee 1, 21335 Lüneburg, Germany
e-mail: olga.abramova@leuphana.de

A. Baumann
Weizenbaum Institute for the Networked Society and University
of Potsdam, Hardenberstrasse 32, 10623 Berlin, Germany
e-mail: annika.baumann@uni-potsdam.de

H. Krasnova
Weizenbaum Institute for the Networked Society and University
of Potsdam, Hardenberstrasse 32, 10623 Berlin, Germany
e-mail: krasnova@uni-potsdam.de

E. Jussupow
Technical University of Darmstadt, Hochschulstrasse,
164289 Darmstadt, Germany
e-mail: ekaterina.jussupow@tu-darmstadt.de

C. Legner
Department of Information Systems, University of Lausanne,
Quartier Centre, 1015 Lausanne, Switzerland
e-mail: christine.legner@unil.ch

A. Meythaler
Weizenbaum Institute for the Networked Society and University
of Potsdam, Hardenberstrasse 32, 10623 Berlin, Germany
e-mail: antonia.meythaler@uni-potsdam.de

O. Müller
Department of Information Systems, Paderborn University,
Warburger Str. 100, 33098 Paderborn, Germany
e-mail: oliver.mueller@uni-paderborn.de

M. Pinski
Information Systems and Electronic Services, Technical
University of Darmstadt, Hochschulstrasse 1, 64289 Darmstadt,
Germany
e-mail: marc.pinski@gast.tu-darmstadt.de

simplified access to such tools paves the way for their widespread intended use, supporting domains such as finance (Strich et al. 2021), education (Chen 2022), academic research (Sarker et al. 2024), chemistry (Lou and Wu 2021), healthcare (Jussupow et al. 2021; Abdel-Karim et al. 2023), and social media (Salge et al. 2022). Next to benign forms, harmful and even malicious ways of algorithm use are also on the rise. For example, deep learning can generate images, audio, and fake events, such as deepfakes (Vasist and Krishnan 2022). This technology can manipulate a politician's speech, allow someone to become a part of their favorite movie, or present them performing like a professional dancer in a video. Artificially created content, initially recognizable by imperfections, is becoming almost indistinguishable as technology advances. At the same time, public awareness of algorithmic systems, commonly referred to as artificial intelligence (AI) by non-experts today, remains low. For example, a survey of more than 6,000 people in the USA, Canada, the UK, Germany, and Australia (using nationally representative research panels) found that only 62% had seen, read, or heard anything about AI, and the majority self-reported a low understanding of how these systems work (Curtis et al. 2023). When presented with common applications such as traffic navigation apps, social media, and email filters, many were unaware that these technologies relied on AI (Curtis et al. 2023).

To successfully navigate our data- and algorithm-driven society, including an ever-confusing digital sphere, algorithmic literacy has been identified as an essential skill (Burton et al. 2020). Generally, algorithmic literacy can be seen as the capability of humans to understand and effectively interact with algorithmic systems (Benbya et al. 2024). Despite advancements on the topic made in IS research (Pinski and Benlian 2024; Wang et al. 2022) and related fields of cognitive psychology (Lintner 2024), media (Dogruel et al. 2022; Oeldorf-Hirsch and Neubaum 2023), and marketing (Tully et al. 2025), many open questions remain unresolved. In particular:

(1) How can algorithmic literacy be defined? How can it be distinguished from related concepts? Does the concept encompass multiple forms of algorithmic literacy?
(2) What methods are most suitable for measurement: objective scales, subjective assessments, or a combination of both?
(3) How can we promote and enable algorithmic literacy? Who should be educated, and at what stages of life? How can we evaluate whether algorithmic literacy has been achieved? What is the minimum set of skills required for algorithmic literacy? Should the expected level of proficiency vary based on an individual's responsibilities and roles? Is there a need for a certification body similar to standardized language and math tests to validate algorithmic literacy?

A panel discussion at the 19th International Conference on Wirtschaftsinformatik (WI 2024) in Würzburg, Germany, on September 18, 2024, offered a forum for discussion and clarification on these open questions. This paper is organized as follows. After describing the composition of the panel (Sect. 1.2), we summarize the points made by the panelists regarding three core themes: defining algorithmic literacy (Sect. 2.1), measuring algorithmic literacy (Sect. 2.2), and strategies for enhancing algorithmic literacy (Sect. 2.3). In Sect. 3, we present the takeaways that emerged from the panel discussion.

1.2 Organization of the Panel and Panelists

The panel was organized by Irina Heimbach, Olga Abramova, Annika Baumann, and Hanna Krasnova. The panel was moderated jointly by Irina Heimbach and Olga Abramova. On the expert side, five IS scholars shared their views on algorithmic literacy issues, namely Ekaterina Jussupow, Christine Legner, Antonia Meythaler, Oliver Müller, and Marc Pinski. Christine Legner and Oliver Müller provided the organizational perspective, while Marc Pinski, Ekaterina Jussupow, and Antonia Meythaler offered an individual user perspective. In what follows, we summarize the panelists' comments on three main themes of the discussion: the conceptualization, measurement, and education of algorithmic literacy.

2 Panel Discussion Summary

2.1 Concept and Definition of Algorithmic Literacy

The progression of literacy concepts has evolved in response to technological advancements. Initially, the focus was on *computer literacy* (Tsai et al. 2021), which was central to navigating the early digital landscape. With the introduction of the internet, the discourse expanded to include *internet literacy*, addressing the skills necessary to effectively use online resources (Dinev and Hart 2004). Subsequently, the emergence of social media platforms brought attention to *information privacy literacy*, emphasizing the need to understand and manage personal data (Dinev 2024). As digital technologies continued to advance, *data literacy* became a key area of focus, highlighting the ability to read, work, analyze, and argue with data (D'Ignazio and Bhargava 2015, Lefebvre and Legner 2024). Most recently, since the spread of AI across industries and especially the public release of ChatGPT in November 2022, the discussion has shifted toward *AI literacy* (Ng et al. 2021, Pinski and Benlian 2024) and *algorithmic literacy* (Oeldorf-Hirsch and Neubaum 2025), with algorithms being the foundational instructions that make (AI) possible.

An algorithm is a set of mathematical instructions or rules that, especially if given to a computer, will help calculate an answer to a problem (Cambridge Dictionary 2025). The conceptualization of 'algorithmic literacy' is predominantly shaped by contributions from communication researchers, who define algorithmic literacy as "being aware of the use of algorithms in online applications, platforms, and services, knowing how algorithms work, being able to critically evaluate algorithmic decision-making as well as having the skills to cope with or even influence algorithmic operations" (Dogruel et al. 2022, p. 118). Thus, the emphasis within communication science is on the application of algorithms on social media platforms (Oelderich-Hirsch and Neubauer 2023). This perspective examines users' understanding of algorithmic processes, such as why certain posts appear on their Facebook feeds — e.g., why a post from one friend is visible while another's is not — or how product recommendations are generated (Heimbach et al. 2015b, 2015a).

At the same time, algorithms extend far beyond social media applications, encompassing a diverse range of areas. For instance, algorithms are central to predictive analytics, which involves forecasting outcomes based on data. Furthermore, the literature on algorithm aversion and overreliance on AI-generated suggestions highlights the critical need for algorithmic literacy (Burton et al. 2020). Algorithmic literacy aims to enhance individuals' understanding of algorithms, potentially serving as a remedy to mitigate both aversion to and excessive dependence on algorithmic recommendations. In the absence of a clear definition of algorithmic literacy in the field of Information Systems research, we kicked off the discussion by asking our panelists to share their understanding of the concept. Table 1 summarizes the panelists' views on algorithmic literacy.

2.2 Measurement of Algorithmic Literacy

Although research increasingly calls for ways to improve AI competencies (Tarafdar et al. 2019), there are no mature instruments available to measure AI literacy due to the high variation in its conceptualizations. The two main approaches to assessing algorithmic literacy are subjective and simple objective measures (Dogruel et al. 2022; Wang et al. 2022). Despite the ease-of-use advantage, subjective scales are prone to over- or underestimation (Mabe and West 1982). Especially in high-stakes decisions, such as medical diagnosis (Ahsen et al. 2019) or criminal justice, one cannot reasonably rely on a workforce whose skills have undergone only subjective assessments. On the other hand, objective scales appear to be very much oriented towards IT professionals (Weber et al. 2023; Markus et al. 2025); for review, see (Lintner 2024) (Table 2).

2.3 Enhancing Algorithmic Literacy

Besides properly defining and measuring algorithmic literacy, another question remains: How can individuals be educated on interacting effectively and responsibly with algorithm systems? As the noticeable and hidden interactions with algorithmic systems become increasingly embedded in daily life, from social media platforms (Kim 2017) to generative AI tools like ChatGPT (Teubner et al. 2023), the ability to critically engage with these technologies is more vital than ever. However, the question of how best to provide the necessary knowledge and skill set remains an open area of research (Oeldorf-Hirsch and Neubaum 2023) (Table 3).

This challenge extends beyond personal digital interactions into the professional sphere, where algorithmic systems increasingly influence work activities across industries (Benlian et al. 2022). While the general awareness of algorithms and their applications is growing (Klawitter and Hargittai 2018), there is a risk that disparities in algorithmic literacy could contribute to a new form of digital divide (Gran et al. 2021). Not least, algorithmic literacy has been recognized as a core competency for navigating the complexities of a digital world shaped by automation and data-driven systems (Spurava and Kotilainen 2023). Therefore, identifying ways to enhance algorithmic literacy across demographics without leaving anyone behind will significantly challenge society and educational institutions, making it a valuable aspect of research discussions.

3 Conclusions and Key Takeaways

This panel featured prominent scholars from Germany and Switzerland who shared their perspectives on algorithmic literacy and their experiences with implementing it. The panel's composition offered diverse perspectives, from insights on leading a data competence center and executive education to researchers' views on understanding the average user's perception. The panelists agreed that algorithmic literacy exists on a spectrum, rather than being a binary state of being literate or illiterate. The required level/degree of algorithmic literacy is determined by the type of user and the consequences of decisions made as a result of human-algorithm interaction. The following list of takeaways has been derived based on the panel discussion.

Table 1 Opinion of the panelists — Disentangling algorithmic literacy from the related concepts

Panelist	Opinion
Ekaterina Jussupow	I find the topic of algorithmic literacy particularly challenging and multifaceted. It encompasses not only an awareness of the existence of algorithms but also an understanding of the underlying data and the specific context in which a system is used. For example, interacting with a conversational AI like ChatGPT requires a different type of literacy than using a predictive AI system in a high-stakes domain like medicine, where professionals must integrate and critically assess system outputs alongside their own expertise. The idea to develop a universal framework for algorithmic literacy is appealing, but it risks overlooking the nuances of specific socio-technical systems and technological artifacts with their specific affordances. Scientifically, my main struggle lies in defining competences across these varied contexts. In my view, a key competence is the ability to critically reflect on the output a system provides — understanding its limitations, how it arrived at its conclusions, and how those conclusions relate to one's own domain knowledge. This reflective capacity is central to the meaningful and responsible use of AI systems as a particular case of algorithmic systems.
Oliver Müller	Reflecting on my own recent research, it becomes clear that there is a lack of consistency in how the community conceptualizes related literacies, ranging from data literacy and statistical literacy to graph literacy and, more recently, AI literacy. Actually, in each of our last three studies, we employed a different „literacy", despite all the studies focusing broadly on algorithmic literacy. This inconsistency raises important questions about the conceptual boundaries between these literacies. One potential distinction could be that data and statistical literacy emphasize understanding inputs and outputs — such as data visualizations — whereas algorithmic or AI literacy also focuses on the internal processes or logic of an intelligent system. From this perspective, it may be useful to conceptualize algorithmic literacy as having two dimensions: one focused on interpreting and evaluating system inputs and outputs (as in data literacy), and another focused on understanding the procedural aspects. Furthermore, as discussed earlier, most definitions of algorithmic literacy focus on individuals as *users* or consumers of algorithms. However, many of our clients (e.g., students) are also *producers* of such systems. In this sense, the concept of literacy — as traditionally involving both reading and writing — should be extended to include the ability to build or design algorithmic systems. In educational contexts, especially, fostering this "writing" capacity is essential and should be a more explicit facet of algorithmic literacy.
Christine Legner	The relationship between data literacy and algorithmic literacy is complex and deeply interlinked. While they can be seen as distinct constructs, one could also argue that data literacy forms a foundational sub-component of algorithmic literacy. From a practical standpoint, data literacy may act as a differentiator — an essential competency that warrants particular attention. There is a well-established body of literature defining data literacy as the ability to read, work with, analyze, and argue with data. This definition encompasses a broad spectrum of skills and behaviors, including technical competencies as well as ethical and value-based dimensions. For example, research in the educational domain, such as the work by Katarina Schüller, highlights both the technical aspects — like identifying use cases, collecting, and processing data — and interpretive aspects, such as data visualization, storytelling, and critical evaluation. While data literacy has traditionally been aligned with descriptive analytics and big data use, its scope can and should be expanded to include algorithmic understanding as part of the analytical process. In our research on corporate data literacy programs, we've observed that such initiatives vary significantly in form and nomenclature — sometimes presented as data literacy, digital literacy, analytics literacy, or even AI and data literacy. This variation underscores how interconnected these literacies are within broader digital competencies. Another critical insight is the need to recognize different user profiles or "personas" within an organization. Not everyone requires the same depth of skill. We typically identify three categories: general users (amateurs), domain-specific professionals (e.g., marketing or supply chain analysts), and data experts (e.g., data engineers, analytics specialists). Each group has distinct learning needs and proficiency levels. Therefore, any literacy framework, whether focused on data, algorithmic, or digital competencies, must be adaptable to these varying levels of expertise and tailored to specific application domains.
Marc Pinski	A point worth raising in the discussion on literacy is the scope and limits of the concept itself. While literacy is often framed as encompassing both "reading" and "writing", this definition can quickly become overly broad when applied to algorithmic contexts. For instance, including advanced programming skills — such as coding in C++ — under the umbrella of "algorithmic literacy" may stretch the concept beyond its intended audience. From my perspective, literacy is more appropriate as a framework for non-experts or laypeople, encompassing foundational skills and basic conceptual understanding rather than professional-level competencies. It is important to distinguish between the literacy required by the general public — such as having a basic understanding of how algorithms influence smartphone content — and the deeper technical skills required by professionals who work directly with algorithmic systems. Literacy implies a set of essential, widely shared skills that everyone in a modern society should possess to navigate daily life. While some level of "writing" — in the sense of being able to conceptualize or modify simple algorithmic structures — may be relevant, we should be careful not to conflate this with full-scale programming or system development. A differentiated approach that separates basic algorithmic literacy from expert-level algorithmic skills is therefore necessary.

Table 2 Opinion of the panelists — Measurement of algorithmic literacy

Panelist	Opinion
Marc Pinski	There are three challenges to measuring algorithmic literacy. First, literacy is a complex construct per se. Subjective assessments rely on self-perception, which can be inaccurate due to cognitive biases like the Dunning-Kruger effect, while objective measures tend to be too narrow and validate specific knowledge rather than broader skills. Against this background, behavior-based assessments, i.e., observing how users actually interact with algorithmic systems, represent a promising alternative. Second, rapid technological progress quickly renders existing measurement tools outdated. Consider ChatGPT and prompting skills that have become extremely relevant. Third, the concept of algorithmic literacy is broad. To be meaningful, any measurement tool requires a precise definition and context, e.g., medical, engineering, or customer service.
Oliver Müller	I advocate using objective, scenario-based testing rather than subjective scales, similar to the established tests used to assess statistical or graph literacy. One could ask people to interpret input-processing-output relations of, for example, recommender systems on social media or e-commerce platforms to evaluate their understanding of how data and algorithms are interrelated.
Christine Legner	Certifications related to algorithmic and data literacy already exist, particularly in professional and educational contexts. These include interpreting algorithmic outputs and assessing the quality of training data, such as bias identification. I believe that such evaluations are important and will likely become more prevalent, if they are not already, particularly in areas involving learning-based systems. We observe high demand among professionals for upskilling and obtaining certifications in data science and data management, especially in executive education. Instead of relying on perceived literacy, I favor objective, example-based assessments covering areas such as data analysis and interpretation, and evaluating trustworthy data sources.

Table 3 Opinion of the panelists — Enhancing algorithmic literacy

Ekaterina Jussupow	Maintaining a balance between structured education and general awareness is important. While executive education and formal training remain valuable, it is necessary to provide the public and schools with basic education about algorithms. This will ensure that algorithmic literacy reaches everyone, as some fundamental concepts are sometimes not widely understood (e.g., biases). People naturally develop mental models of how algorithms work through interactions with the system, but these models may not always be accurate and are often not explicitly reflected upon. Essential algorithmic knowledge will equip individuals with the tools to better understand algorithmic systems' capabilities and limitations.
Christine Legner	Algorithmic literacy can be a challenge due to evolving algorithms and complex explanations. End-users should be able to understand the basic logic behind algorithmic systems, such as how data input shapes outcomes, their probabilistic nature, and potential biases. Algorithmic literacy should be framed within a broader digital context, providing a necessary level of abstraction for everyday users while allowing for deeper technical knowledge where needed. Educational efforts should cater to different audiences with varying needs. Generic online courses are insufficient. Instead, training should be integrated into real-world contexts, making algorithmic literacy directly applicable to users' roles and decisions.
Antonia Meythaler	Some domains operate with opaque and constantly changing systems. Educating users on the presence of algorithms and their broader implications is essential for algorithmic literacy. Due to the secretive nature of many algorithms, empowering users by making algorithms more transparent is key, though challenging. Regulation can play a role in ensuring greater transparency. Algorithmic literacy should be introduced into school curricula early to prepare users to navigate digital environments critically.
Oliver Müller	The necessary depth of algorithmic literacy depends on the audience. While some may need a deeper understanding, others can interact with complex systems without fully understanding how they work. Also, concerns about algorithmic decision-making might fade over time, as fears surrounding other technologies have in the past. Another aspect is the ability to code. It would be valuable to introduce coding education at an early age, making the knowledge accessible by using relatable terms and hands-on activities (e.g., robotics). In my view, making coding a mandatory subject in schools could help foster algorithmic literacy from an early stage.
Marc Pinski	While in-depth knowledge of algorithms may not be necessary, understanding their core properties and implications is crucial for interpreting their generated outputs responsibly.

1. *The concept of algorithmic literacy* is still emerging, multifaceted, and context-dependent. In addition to awareness of algorithms, algorithmic literacy requires a critical understanding of data inputs, internal reasoning, output interpretation, and domain-specific applications. Thus, algorithmic literacy builds upon related literacies, such as *statistical*, *graph*, *computer,* and *data literacy*, with data literacy often serving as a foundational component. The distinction between "reading" (interpreting outputs) and "writing" (designing or understanding algorithms) is essential, though caution is advised against overextending the concept of literacy to encompass expert programming skills. Furthermore, algorithmic literacy must be adaptable to different user profiles to accommodate the varying needs of lay users, domain professionals, and technical experts.

2. *Measuring algorithmic literacy* poses several challenges, including the construct's inherent complexity, the limitations of subjective self-assessments, and the limited scope of many objective tests. Additionally, the broad and context-dependent nature of algorithmic literacy necessitates that measurement tools be tailored to specific domains, such as healthcare or customer service. At the same time, the rapid evolution of technology can quickly render existing tools obsolete. For instance, the emergence of generative AI has made prompting skills more important. In this context, objective, scenario-based assessments, such as interpreting algorithmic outputs on social media or evaluating data quality, are favored over subjective scales. At the same time, behavior-based assessments, which observe users' interactions with algorithmic systems, are seen as a promising alternative. Furthermore, certifications in algorithmic and data literacy are viewed as valuable for promoting rigorous, practical competencies in understanding and managing algorithmic systems.
3. *Enhancing algorithmic literacy* requires a balanced approach that combines structured education with accessible, informal learning to reach a broad audience. While formal training, such as executive education and domain-specific programs, is important for professionals, initiatives focused on general awareness are essential to equip all individuals with a foundational understanding of algorithms and related concepts such as data bias, privacy risks, and probabilistic outputs. Importantly, educational efforts should be integrated into real-world scenarios rather than relying solely on generic online courses. Incorporating coding and algorithmic thinking into school curricula from an early age can build foundational knowledge and demystify algorithms over time. At the same time, transparency in algorithmic systems, supported by regulatory efforts, can empower users, even though some complexity and opacity will inevitably remain.

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