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# Algorithmic Literacy, AI Literacy and Responsible Generative AI Literacy

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# Algorithmic Literacy, AI Literacy and Responsible Generative AI Literacy

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**ABSTRACT**
The pervasive impact of Artificial Intelligence on workers and citizens implies the need for AI literacy, but it is an elusive concept. The purpose of the paper is to review definitions of algorithmic, AI and generative AI literacy. In depth of analysis is presented of conceptualisations of AI literacy coming from different perspectives, such as media studies, HCI, technology and education. The paper then outlines a definition of responsible generative AI literacy that conceives it as more than effective prompting.

**KEYWORDS**
Artificial Intelligence; AI; AI literacy; Algorithmic literacy; Generative AI; Responsible AI

## Introduction

AI is being applied in a wide range of contexts from health and science, to farming and finance. It is being used in multiple ways in everyday knowledge work tasks such as in search and recommendation, in summarization, in writing, transcription and in translation. It is affecting many workplaces so that AI literacy is likely to become seen as a component of employability skills. Further, because of its impact on society and on media and communication in particular it has implications for democracy, and so for every citizen and member of the public. Thus, it is recognized that it is important to try and define what the public as workers and citizens need to know about AI.

Yet defining the scope of AI literacy is hard. As a general purpose technology, that is really an umbrella term for a number of techniques, AI looks different in different contexts. It is also an evolving idea. For example, generative AI has shifted our conceptualization of AI dramatically. Furthermore, there is a need for some understanding of the technologies, but clearly AI literacy is not reducible to technical skills. AI has a philosophical and ethical dimensions that are hard to fully relate to technologies. There is a need to learn underlying persistent skills not solely how to use specific tools. However, it is also likely that

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people may need practical knowledge and experience, and so be empowered to use AI effectively, as well as theoretical knowledge. There is a need to define AI literacy for different professional groups, including for those working directly with AI, including information professionals.

This drive to define AI literacy focuses on the "user" dimension, if user is the right term in an AI context, given that with AI it is also seen as potentially a form of collaboration, akin to that with another human person. Logically, the focus on defining AI literacy is in parallel with the call for AI systems that are less opaque and more explainable and transparent, as a responsibility of those designing and implementing systems. If the social demands to make AI less opaque are successful, the need for certain aspects of AI literacy might decline or at least change.

The purpose of this paper is to reflect on some of the major attempts to define AI literacy and suggest a model of responsible generative AI literacy. It begins by exploring the relation between AI and algorithmic literacy. In this context it considers the challenges of defining and raising AI literacy at all. It then reviews several major attempts to define AI literacy from different perspectives. It then considers how responsible generative AI literacy might be defined. Moving beyond generative AI literacy as prompt engineering, it considers the various components that make this up including awareness of ethical issues, societal and individual impacts.

## AI and algorithmic literacy

There are several different approaches to defining AI literacy. It is often claimed that AI could be linked to profound changes in the perception of the human condition and consequent society. If AI overtakes human intelligence it presents a change in human life or an existential risk. If this is accepted AI literacy is a hugely important topic. In this case the definition might be extensive. An example of this type of definition is proposed by Yi (2021):

> "AI literacy is an individual's ability to not only utilize AI, but to also critically recognize changing cultures. Furthermore, based on the basis of understanding AI, AI literacy allows the individual to design their own life. In other words, AI literacy is the basic ability to become a subjective human in the AI era."

This is interesting, but hard to operationalize. It implies a broad response to AI as a deep cultural phenomenon. However, most definitions of AI literacy are much more specific, and often center on technical understanding and application. Kong et al. (2021) suggest it is composed of three elements: understanding of AI concepts (such as machine learning, decision trees etc), the ability to evaluate the application of AI concepts, and the ability to apply the concepts to real world problems.

A widely cited, more elaborated definition is offered by Long and Magerko (2020):

> "We define AI literacy as a set of competencies that enables individuals to critically evaluate AI technologies; communicate and collaborate effectively with AI; and use AI as a tool online, at home, and in the workplace."

Here AI literacy is seen as primarily about successful use and evaluation of AI technologies; though the further detail of their model (discussed below) goes much beyond this. Their paper also develops design considerations to address the issue of AI opacity. This reflects that the authors are speaking to the HCI community, with its focus on improving people's interaction with systems.

Predating work using the AI literacy label there is already an important literature around algorithmic literacy, that is not always fully integrated into discussion. AI literacy tends to focus on technical understanding, with some criticality, and often assumes a direct, explicit encounter between humans and an AI system. In contrast, algorithmic literacy focuses on the presence of AI buried within infrastructures, especially of commercial platforms. Whenever we receive information pushed at us by recommendation, or search, or use social media or streaming platforms much of the content is filtered by algorithms. This removes some "noise" and offers useful personalization and recommendation services, but it also may have filter bubble effects, in ways that are often quite hidden, even deliberately secretive. Biases in information can be reproduced. There is an impact on privacy implied by the surveillance required to offer adaptivity. There is a potential for manipulation of humans and deliberate use of strategies to addict users (Grizzle et al., 2021). Algorithmic literacy is about individual users having some understanding and ability to respond or even control over this phenomenon. It is rooted in a critical perspective on the power of current social media platforms, and strongly related to wider media literacies.

Dogruel et al. (2022) write:

> "Algorithm literacy can thus be defined 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."

This dimension could usefully be integrated into AI literacy discussions. The nearest to doing so are Ridley and Pawlick-Potts (2021) when they suggest that:

> "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."

## Obstacles to defining and raising AI literacy

There are a number of serious challenges to raising AI literacy. Some aspects of this are that AI is an umbrella term for multiple technologies and applications, that it continues to evolve, and it relies on difficult to understand methods, and that, indeed, some aspects of its outputs may not be fully understood even by its designers.

AI has multiple dimensions and applications. Perhaps it is too ambitious to define AI literacy in general. Thus Carolus et al. (2023) develop a definition of AI literacy specifically for voice systems. In addition, AI itself is evolving making it hard to define AI literacy definitively. For example, the advent of ChatGPT and generative AI have shifted perceptions of AI quite radically during 2023. As the definition of AI has a value it is a focus of contestation, such as between system suppliers. The complex and changing nature of AI makes it hard to define and to explain. Furthermore, it could be argued that AI is inherently hard to understand because of its reliance on methods most people are not trained in, such as statistics and advanced computation.

One debate in the literature is how AI literacy might relate to IT literacy. It does seem to shift attention away from coding as core to AI literacy, but it must surely be rooted in some sort of computational literacy. Some aspects of AI are inherently hard to explain e.g. outputs from AI that has learned from data may not be able to be explained even by those developing the application.

AI has received huge media coverage in the last few years, and, in the longer-term cultural fascination and horror with AI could be seen as useful in making people aware of AI. However, it may not be so helpful in raising understanding, given that it is generally presented in the form of robots who can scarcely be differentiated from humans (general AI) and often in dystopian visions. Emotive responses revolving such cultural fascination could be seen as posing a barrier to clear explanation and understanding. Certainly the popular media presentation of AI blurs distinctions between different technologies (Long & Magerko, 2020). Attempts to measure AI literacy "objectively" through scales (Carolus et al., 2023) may therefore be premature.

The algorithmic literacy literature identifies further barriers to this specific dimension of AI literacy:

- The idea is new, and users have not been educated in it. Folk theories that have developed among user communities may be misleading.
- The working of AI is often invisible and not directly acknowledged to users.
- Often the algorithms in use are a commercial secret, and are frequently updated.
- Each platform is different.
- It is often assumed platforms' working is "neutral", e.g. simply personalizing content, when they are not.
- Algorithms have a dimension of deliberately creating addiction, which means understanding how they control behavior is important.
- Users find the filtering useful, are not very concerned by the privacy risk, or see it as an inevitable cost of using free services.
- Researchers do not themselves know what algorithms are in use so it is impossible to measure literacy precisely.

## Some attempts to define AI literacy

### *Five Big ideas*

An early formulation of AI literacy was in the form of the five Big ideas:

1. Big Idea #1 – Perception. Computers perceive the world through sensors that are akin to human senses.
2. Big Idea #2 – Representation & Reasoning. Agents maintain representations of the world, and use them for reasoning.
3. Big Idea #3 – Learning. Computers can learn from data, generally by statistical inference.
4. Big Idea #4 – Natural Interaction. Intelligent agents require many types of knowledge to interact naturally with humans.
5. Big Idea #5 – Societal Impact. Artificial Intelligence can impact society in both positive and negative ways.

The strength of this approach is that it focuses on fundamental concepts that offer general insights, as a platform for understanding specific systems. It is conceptual but backed up with Learning Objectives for people at different ages. However, as an approach it seems somewhat abstract and distant from real-life applications. It supplies a general knowledge that prevents false assumptions being made about AI solutions; but it is hard to relate to specific applications. It also largely lacks the more sophisticated critical dimensions developed in algorithmic literacy work.

### *Long and Magerko (2020): AI literacy*

At the time of writing the most widely cited model of AI literacy is that proposed by Long and Magerko (2020) (Table 1). The authors break AI literacy down under five headings, with 17 components under those headings:

1. What AI is – this is knowledge such as how to recognize AI when it is encountered and understanding distinctions between general and narrow AI.
2. What it can do – this consists of differentiating the tasks AI is good at doing from those it is not good at, and also being able to imagine future uses, reflecting the evolving nature of AI.
3. How AI works – includes ideas such as representation (from the big 5) and has an emphasis on data literacy, referring to Calzada Prado and Marzal (2013) for a definition of this, but emphasizing learning from data and the need for critical interpretation of data.
4. How it should be used – under which ethics is placed.
5. How people perceive it.

In addition to defining these elements of AI literacy, the paper builds up considerations for system design, recognizing this dimension of the issue in making AI transparent. Long and Magerko (2020) definition is a rather wide ranging and inclusive, as suggested by item 3 which emphasizes the Interdisciplinarity behind the development of AI. The emphasis on imagining future uses (item 6) recognizes the rapidly changing nature of the technology and also avoids a reductive approach. Given the data driven nature of current AI, it is not surprising that data literacy has several mentions, including referencing the Calzada Prado and Marzal (2013) definition.

Some elements seem to be more contestable. The difficulties of defining AI itself may be part of the issue. For example, one aspect of "what AI is" is understanding the nature of intelligence in general (item 2). One wonders how necessary this is to a practical understanding of a specific AI tool or system. Also, the definition begs the question of how knowledge is acquired. For example, recognizing that AI is in use (item 1) is not easy, as the algorithmic literacy literature shows. There are what we might consider missing elements such as legal dimensions (though some elements of this are in the data literacy model referenced). From a purely technical

**Table 1.** AI literacy as defined by Long and Magerko (2020).

| | |
|---|---|
| What is AI? | |
| 1. Recognizing AI | Distinguish between technological artifacts that use and do not use AI. |
| 2. Understanding Intelligence | Critically analyze and discuss features that make an entity "intelligent", including discussing differences between human, animal, and machine intelligence. |
| 3. Interdisciplinarity | Recognize that there are many ways to think about and develop "intelligent" machines. Identify a variety of technologies that use AI, including technology spanning cognitive systems, robotics, and ML. |
| 4. General vs. Narrow | Distinguish between general and narrow AI. |
| What can AI do? | |
| 5. AI's Strengths & Weaknesses | Identify problem types that AI excels at and problems that are more challenging for AI. Use this information to determine when it is appropriate to use AI and when to leverage human skills. |
| 6. Imagine Future AI | Imagine possible future applications of AI and consider the effects of such applications on the world. |
| How does AI work? | |
| 7. Representations | Understand what a knowledge representation is and describe some examples of knowledge representations. |
| 8. Decision-Making | Recognize and describe examples of how computers reason and make decisions. |
| 9. Machine Learning Steps | Understand the steps involved in machine learning and the practices and challenges that each step entails. |
| 10. Human Role in AI | Recognize that humans play an important role in programming, choosing models, and fine-tuning AI systems. |
| 11. Data Literacy | Understand basic data literacy concepts such as those outlined in Calzada Prado and Marzal (2013). |
| 12. Learning from Data | Recognize that computers often learn from data (including one's own data). |
| 13. Critically Interpreting Data | Understand that data cannot be taken at face-value and requires interpretation. Describe how the training examples provided in an initial dataset can affect the results of an algorithm. |
| 14. Action & Reaction | Understand that some AI systems have the ability to physically act on the world. This action can be directed by higher-level reasoning (e.g. walking along a planned path) or it can be reactive (e.g. jumping backwards to avoid a sensed obstacle). |
| 15. Sensors | Understand what sensors are, recognize that computers perceive the world using sensors, and identify sensors on a variety of devices. Recognize that different sensors support different types of representation and reasoning about the world. |
| How should AI be used? | |
| 16. Ethics | Identify and describe different perspectives on the key ethical issues surrounding AI (i.e. privacy, employment, misinformation, the singularity, ethical decision making, diversity, bias, transparency, accountability). |
| How do people perceive AI? | |
| 17. Programmability | Understand that agents are programmable. |

point of view, one could also see the list as also a little disorganized, e.g. the elements of how AI work overlap but it is also hard to see how they inter-relate. There is no emphasis given to one or a number of components over others. Compartmentalizing the ethics dimension (as item 16) from design and on-going maintenance and use, should also be seen as problematic, given the huge debate around AI ethics (Corrêa et al., 2023; Jobin et al., 2019). The need to use AI ethically, safely or "responsibly" is central to AI literacy. There is no sense of different levels of literacy, such as between everyday user and someone involved in design. Many aspects do not seem vital for general user. Most fundamentally, there seems to be limited acknowledgement of the dimension of algorithmic literacy.

There is not much sense of the critical socio-technical informed critique of BigTech that underlies most work in that field. Criticality is treated here as more about evaluating tools or asking questions about data sources, rather than about challenging AI's wider impact in the context of social structures that reproduce inequalities. Nevertheless, Long and Magerko (2020) definition is the dominant model of AI literacy at the time of writing and widely cited by other literature, including nearly all the material about teaching and measuring AI literacy.

### *Pinski and Benlian (2023) the AI literacy scale*

A more recent attempt to articulate a model of AI literacy is by Pinski and Benlian (2023). They propose that it can be defined under six headings, with 28 components (Table 2):

1. Technology knowledge – eg types of technology used and use cases
2. Human actions in AI knowledge – how human actors, with a stress on non programmers, can be involved in AI development and use
3. AI steps knowledge – process of creating AI applications, broken down into three steps: inputs, processing and outputs
4. AI usage experience
5. AI design experience
6. AI literacy knowledge – overall understanding of AI is encapsulated in three elements

Not surprisingly, there are some parallels between this definition and Long and Magerko (2020). For example, Pinski and Benlian (2023) idea of "use cases" parallels Long and Magerko (2020) heading "what AI can be used for". Their AI steps knowledge expand on Long and Magerko (2020) "Machine learning steps". But overall there are many important differences.

A strength of Pinski and Benlian (2023) is that it has a stress on experience as well as knowledge. It immediately strikes one as a more logically constructed and more specific than Long and Magerko (2020) but also therefore less conceptual and more closed. For example, knowledge of use cases seems to be easier to convey than how to recognize AI. As the naming of the "AI steps" heading suggests the focus is on a set of technical processes typical of machine learning projects. This feels more logical than Long and Magerko (2020), but more procedural and less conceptual. While easier to teach a procedural definition a conceptual approach would presumably be more long-lasting type of knowledge, as actual applications change. Fundamentally, Pinski and Benlian (2023) approach seems nearer to defining competencies to be involved in designing AI, so of a

**Table 2.** The AI literacy scale (Pinski & Benlian, 2023).

| | |
|---|---|
| **AI technology knowledge** | |
| TK1 | …of the types of technology that AI is built on |
| TK2 | …of how AI technology and non-AI technology are distinct |
| TK3 | …of use cases for AI technology |
| TK4 | …of the roles that AI technology can have in human-AI interaction |
| **Human actors in AI knowledge** | |
| HK1 | …of which human actors beyond programmers are involved to enable human-AI collaboration |
| HK2 | …of the aspects human actors handle worse than AI |
| HK3 | …of the aspects human actors handle better than AI |
| HK4 | …of the human actors involved to set up and manage human-AI collaborations |
| HK5 | …of the tasks that human actors can assume in human-AI collaboration |
| **AI steps knowledge** | |
| *AI input* | |
| SK1 | …of the input data requirements for AI |
| SK2 | …of how input data is perceived by AI |
| SK3 | …of potential impacts that input data has on AI |
| SK4 | …of which input data types AI can use |
| *AI Processing* | |
| SK5 | …of AI processing methods and models |
| SK6 | …of how information is represented for AI processing |
| SK7 | …of the risks AI processing poses |
| *AI Output* | |
| SK8 | …of why AI processing can be described as a learning process |
| SK9 | …of using AI output and interpreting it |
| SK10 | …of AI output limitations |
| SK11 | …of how to handle AI output |
| SK12 | …of which AI outputs are obtainable with current methods |
| I have experience in… | |
| **AI usage experience** | |
| UE1 | …in interaction with different types of AI, like chatbots, visual recognition agents, etc. |
| UE2 | …in the usage of AI through frequent interactions in my everyday life |
| **AI design experience** | |
| DE1 | …in designing AI models, for example, a neural network |
| DE2 | …in development of AI products |
| **AI literacy (Overall items)** | |
| AIL1 | In general, I know the unique facets of AI and humans and their potential roles in human-AI collaboration |
| AIL2 | I am knowledgeable about the steps involved in AI decision-making |
| AIL3 | Considering all my experience, I am relatively proficient in the field of AI |

professional as opposed to being a "user" or citizen. It is essentially a definition from an IT perspective, as opposed to Long and Magerko (2020) HCI perspective or the media literacy/socio-technical/critical perspective offered by the scholars working on algorithmic literacy. It is partly driven by a desire to measure AI literacy, which requires that each element is specific and so can be operationalized.

There is also far greater emphasis in Pinski and Benlian (2023) on the different ways humans can be involved with AI systems. This tends to be conceived of as a collaboration between an AI and an individual. It is also seen as about users of a system rather than involvement in designing the system. This again sidelines the essential insight of algorithmic literacy that AI is often hidden embedded in an infrastructure, itself shaped by commercial motives, in ways that impact humans even if they are not aware. Nor is there any explicit mention of ethical issues. This is a huge gap, given the current ethical concerns around AI.

### *Markauskaite et al. (2022): AI capabilities*

If we have reviewed AI literacy from technical and HCI perspectives in the previous two sections, Markauskaite et al. (2022) develop a rich set of alternative views from differing educational perspectives. Rooting an analysis in nine different theories of learning/knowledge building they consider what AI capabilities would be needed within each of these lenses (Table 3 below). This produces a fascinatingly complex impression of what capabilities are needed to learn in the context of AI. This opens up the potential for AI literacy to have multiple perspectives, each conceiving the relation to AI differently, and requiring different approaches to how they could be promoted. Most of these remain at quite an abstract level, but they do help us recognize that AI literacy might not be reducible to a measurable "skill".

## Responsible generative AI literacy

The advent of ChatGPT has brought AI to the center of public debate but also dramatically shifted experiences and expectations of AI, such that it is reasonable to ask whether there needs to be a new definition of AI or, at least, a definition of generative AI literacy per se. ChatGPT became popular so quickly for good reason. From conversational prompts coherent text answers are generated. Searching as a conversation is an attractive model. As is also receiving an answer rather than a list of resources that then have to be read and synthesized as in a google search. Generative AI can be used to support a large number of cognitive activities such as brainstorming, structuring ideas, gathering information, writing, refining drafts and proof reading.

Yet ChatGPT, at least in its early manifestation, also posed many informational and ethical problems (Fergusson et al., 2023; Hagendorff, 2024) so that qualifying AI literacy as ethical or responsible becomes essential:

**Table 3.** AI capabilities (Markauskaite et al., 2022).

| Perspective | What AI competency consists of |
|---|---|
| Self regulated learning | "self regulated learning skills to adapt to changes and maintain agency while working with AI" |
| Hybrid cognitive system perspective | "Perform cognitive work where AI is less capable" |
| 4 Cs perspective | "Be creative in uniquely human ways" |
| Sen's capability perspective | "Become deliberate about the use of AI" |
| Human centered AI perspective | "Create AI for human values" |
| Social realist | "Consider and use AI in relation to one's work and a larger system" |
| AI mediated discourse | "Navigate one's own and others' views, mediated by AI" |
| Knowledge artistry | "facilitate collective sensemaking using representational tools" |
| Networked learning | "Learn in the networks of humans and on-human intelligent systems" |

- It "hallucinates" inaccurate information, fails to acknowledges its sources and can even fabricate citations
- It was trained only on data prior to September 2021, so that responses could be out of date.
- It produces statements containing unacknowledged and harmful bias, e.g. studies have shown it has political bias but also reproduces sexist and racist stereotypes (Deshpande et al., 2023; Motoki et al., 2023).
- It is unexplainable because it is not open about what data it was trained on or how it works.
- It is currently impossible to identify that the text it generates is a machine output.

There could also be some generalized impacts on the information culture, such as that:

- It could be used to create misinformation, harmful disinformation and fakes
- It could also be used to accelerate a content creation explosion – leading to even more challenges of information overload – but also potentially to the increased homogenization of content.
- It is "multilingual but monocultural" (Rettberg, 2022) because it is efficient in multiple languages but has American cultural assumptions trained into it
- Better tools are available on subscription, creating inequality in access to its benefits.
- Trained largely on open web data it is bound to under-represent the perspectives of regions and communities that are already under-represented on the web (such as minority languages), and who are also under-represented in AI research (Komminoth, 2023).

It has potential impacts on learning and human skills:

- It could create lazy and superficial human engagement by making knowledge related tasks like note taking and writing too easy.

Other ethics issues

- Privacy is at risk if you share your data with it

Even more fundamentally, there are question marks about the ethics of how it was developed and deployed, and wider societal impacts:

- It may violate intellectual property rights by using copyright material in its training data without permission.

- Very low paid Kenyan workers were asked to view unpleasant material as part of the process of "detoxifying" data that was being input to train ChatGPT (Perrigo, 2023)
- GPT technologies have a huge environmental impact (Ludvigsen, 2022) and AI as a whole is based on exploiting extensive material and human resources (Crawford, 2021)
- Labor displacement is a significant societal impact of AI. The promised productivity gains of AI should not deflect from the impact on changing roles and potential for deskilling or further extraction and control of labor.

Some of these problems are being addressed in later versions of ChatGPT or in other text generation tools such as Gemini or the new Bing, and most certainly in open source alternatives. Many are not inherent to large language models, rather reflect the BigTech's profit seeking drivers. An understanding of a given generative AI application implies a concern with the business model of the supplier, rather than taking it simply as a "tool" (Wheatley & Hervieux, 2023). Given the great AI capabilities of BigTech in terms of resources including data and so their power to define the AI, we anticipate that users need to have awareness of such potential issues. It follows that responsible, ethical use by individuals is vitally important.

### *Literacy for responsible use of generative AI*

Central to much discussion of generative AI literacy is the idea of learning to prompt effectively. This implies techniques as ensuring that prompts define a context/persona for the enquiry (a teacher planning a class for 16 year old children) and define output types (e.g. a bulleted list or a 200 word essay). It is recommended to iterate requests, improving them, and then synthesize results and to ask the generative AI to itself suggest prompts. Such advice appears to be useful across generative AI platforms, albeit they do vary. Lo's (2023) CLEAR model of takes advice about prompting further by offering general principles and emphasizing that learning good prompts is also to learn good communication in general. Prompts that are Concise, Logical, Explicit, Adaptive and Reflective reflect good habits of communication.

Useful though such advice is, a focus on prompts ignores wider issues with generative AI. The ethical dimension is given much greater centrality in Hillier's (2023) proposed AI literacy framework. This has five dimensions: ethical use of AI tools, knowledge of AI affordances, working effectively with AI tools, evaluation of AI output, use and integration into practice. As well as the stress on ethics it also usefully emphasizes the importance of evaluating the outputs of generative AI in the context of phenomena such as hallucination. Annapureddy et al. (2024) identify twelve components of generative AI literacy. Many of the components are similar, such as general knowledge of large language models and an understanding of prompt engineering. But the authors go beyond prompt writing to suggest programming and fine tuning generative AI as an aspect of generative AI literacy, though these seem more like designer than user skills. They also include the ability to identify generative AI created content. Interestingly, they differentiate knowledge of legal aspects, such as of the EU AI act, from ethics concerns as components of AI literacy. They mention the need for the user to go on learning as a relevant competency. Zhao et al. (2024) give great emphasis to the informational, ethical and societal aspects of AI literacy, as well as the pragmatic dimensions of picking the right tool and understanding of how to use it. They also stress the need for reflective awareness of the potential impacts of use of generative AI such as technology dependence or reduced social engagement. They identify the need to understand contextually appropriate uses of AI. Thus the concerns with academic integrity so central for the educational domain, do not apply in the same way in other contexts.

This emergent debate on defining generative AI literacy supports the idea that a specific generative AI literacy is useful. Developing further the model set out in Zhao et al. (2024) this paper suggests that responsible generative AI literacy is composed of four types of knowledge that are needed differentially through the use process. The four types of knowledge are:

1. Theoretical knowledge
   This is the necessary theoretical understanding of generative AI that is need for its responsible use. This rests on wider AI literacy, e.g. to understand generative AI one must understand things like machine learning. It would probably extend preexisting AI literacy because LLMs are not the most widely understood of AI techniques.
2. Ethical knowledge
   This is thinking through one's stance on the key ethical issues relating to generative AI. Actually, many of the ethical issues with generative AI have been perceived to be issues for AI in its previous manifestations too (and often wider technology use) e.g. bias, privacy risks, unequal access. So wider AI literacy contributes here, although some of the issues look different with generative AI (Hagendorff, 2024). As the discussion above indicates the full range of ethical issues would include: IPR issues relating to the legal use of training material; Impact on information culture, misinformation

and disinformation; Social impacts such as through exploitative process of creation, and the impacts on jobs/job enrichment; Equity of access; Environmental impacts; Implications of the undue power of BigTech. There is also a privacy dimension.

3. Pragmatic knowledge
   This is where AI is "just a tool". This is the knowledge used intensively to choose the right tool for a task and use it effectively to gain suitable outputs in a task context. This is the most dynamic aspect of knowledge because of the rapid changes in availability and functionality of AI applications. It is also the highly novel dimension, because previous AI was used in different contexts.
4. Reflective knowledge
   Prior to any use the user should have reflective awareness about themselves and their own needs as a learner, information seeker or other role. The use of generative AI could have untended impacts such as growing dependence, loss of skills, loss of social contact, so being aware of these effects implies reflection on the effects of use (Zhao et al., 2024). This type of knowledge is key to being empowered through AI, an aspiration of much algorithmic and AI literacy.

### *Knowledge through the use process*

Through the process of any particular use (or a general habit of use) these four types of knowledge need to be differentially activated. We split the process into six stages (summarised in Table 4):

1. Prior knowledge. Knowledge of how to use generative AI systems should be rooted in a deeper understanding of AI, its ethics and also one's own learning, information needs or other role related needs.
2. Understanding generative AI. This understanding has components of all types of knowledge: A theoretical knowledge of how generative AI tools work; an appreciation of their potential ethical impacts; awareness of the range of tools available; an appreciation of the potential individual impacts. This is a key sensitizing step that enables responsible use, but may often be lacking. For example, the user misunderstands the nature of LLMs and assumes that it is a single point of truth rather than a writing tool. They do not appreciate the range of ethical issues. They may not be aware of the widest range of tools, from a pragmatic perspective. They may not think about the potential impacts on themselves.
3. Picking the right tool for the task. This has two dimensions. Firstly, knowing the range of possible uses. The second is applying one's knowledge to decide which tool is ethical to use.

Table 4. The knowledge components of generative AI literacy.

| Knowledge types > | Theoretical knowledge | Ethical knowledge | Pragmatic knowledge | Reflective knowledge |
|---|---|---|---|---|
| **Prior knowledge >** | Computational knowledge | Ethical and value stance | | One's own learning and information needs |
| **Use process knowledge v** | | | | |
| **Understanding generative AI** | How LLMs work | Ethical impacts of LLMs | Range of tools available | The potential individual impacts |
| **Picking the right tool for task** | | Check tools against ethical issues | Types of uses possible | |
| **Use** | Prompt engineering theory | Integrity in use; Safety awareness | Knowledge of prompting with particular tool<br>Critical evaluation of outputs | |
| **Declaring use appropriately** | | Integrity in use of generative AI | | |
| **Evaluating use** | Building theoretical knowledge | Ethical insights from use | Improving techniques of use | Think about impacts of use on dependency, learning, social connections |

4. Use. Here the emphasis shifts to pragmatic knowledge of how to use generative AI as a tool effectively. This implies some theoretical knowledge of prompt engineering principles, but is probably primarily about applying understanding of how a tool best works. It also implies awareness of the informational weaknesses of generative AI such as information inaccuracy and bias. This calls for a critical questioning of outputs. Of course, such use has to be contextually ethical, so rests on ethical knowledge. For example, while the tool could generate an entire essay, it would be unethical to use it in this way in a formal learning context. Another ethical dimension is protecting one's own privacy.
5. Declaring use appropriately. Depending on context, how generative AI has been used should be declared. For example, in an academic context it is about citing its use in an institutionally approved way. In a workplace context it would still be useful to explain the role of generative AI in generating a text. In some contexts no acknowledgment might be necessary.
6. Evaluating use. As with any process there should be a period of reflection before the next round of action: new knowledge can be added to the four areas of relevant knowledge. This suggests questions such as: What has been learned that could make use more effective in the future? How does this knowledge fit into prior understanding of the theory of AI/generative AI? Critically there should be

reflection on how use of the generative AI has impacted the self: we know that there are fears about the unintended effects of using generative AI e.g. missing out on learning, growing dependence and loss of social interaction.

What has been discussed is a user-oriented definition of AI literacy. The literacies required to build or even recommend/support use of generative AI tools might be a little different.

This is a process oriented definition of generative AI literacy. Although in an ideal world the process should start with building logically prior knowledge, this may not happen in reality. It may be that as they use the "tools", users begin to build the more underlying forms of prior knowledge. But it does seem likely that as users we learn ideas from previous systems. So we inherit relevant knowledge base from understanding of strengths and weaknesses of prior AI for recommendations as we encounter relatively new technologies.

The model seeks to balance an appreciation of the more theoretical types of knowledge of the technology with pragmatic knowledge of use of particular applications. Ethics are given priority by being highlighted in a key strand; as are reflecting on the personal impacts of AI use. The complexity of AI literacy is revealed from this analysis. It is not intended to be the basis of a tool to measure AI literacy (e.g. through a self evaluation questionnaire) which is a problematically reductive approach. However, the analysis can be used to think about the weak points in most generative AI use. For example, it might be common for casual users to lack a real understanding of the nature of generative AI, a limited appreciation of the ethics and little awareness of the impacts on the self. Even pragmatic knowledge could be weak without prompt engineering skills. The model can also be used to evaluate guides to AI use. Many fall short in the area of ethics, because they do not encourage the user to think about the wide range of ethical concerns around AI prior to use. They may focus purely on how to engineer effective prompts. Nor do they invite the user to reflect on the impact of use on their own experiences, such as in learning.

An assumption of the model is that the generative AI is a free-standing tool, rather than a function called within an application or platform. If the latter generative AI use has to be evaluated in a wider context. This is a highly significant proviso, because the likely direction of travel is for generative AI to be embedded in other tools. It also focuses on text generation tools. Generative AI literacy for systems that create images or videos might have other dimensions.

## Conclusion

This paper has sought to provide an overview of some of the main perspectives on algorithmic and AI literacy, including generative AI literacy. In-depth analysis is offered of some different types of definitions. The paper has sought to show that many of the differences are attributable to the domain of research where that definition originates be it HCI, technology, education or media literacy studies. The paper moved on to offer a definition of responsible generative AI literacy that goes beyond improved prompting (however important that is) to consider wider issues such as the ethical dimensions, societal impacts and individual effects. Given that AI is an umbrella concept encompassing multiple technologies, it is likely that AI literacy will evolve further.

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