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Rethinking the entwinement between artificial intelligence and human learning: What capabilities do learners need for a world with AI?

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ABSTRACT

The proliferation of AI in many aspects of human life—from personal leisure, to collaborative professional work, to global policy decisions—poses a sharp question about how to prepare people for an interconnected, fast-changing world which is increasingly becoming saturated with technological devices and agentic machines. What kinds of capabilities do people need in a world infused with AI? How can we conceptualise these capabilities? How can we help learners develop them? How can we empirically study and assess their development? With this paper, we open the discussion by adopting a dialogical knowledge-making approach. Our team of 11 co-authors participated in an orchestrated written discussion. Engaging in a semi-independent and semi-joint written polylogue, we assembled a pool of ideas of what these capabilities are and how learners could be helped to develop them. Simultaneously, we discussed conceptual and methodological ideas that would enable us to test and refine our hypothetical views. In synthesising these ideas, we propose that there is a need to move beyond AI-centred views of capabilities and consider the ecology of technology, cognition, social interaction, and values.

1. Introduction

The appearance of computers in the workplaces at the turn of the 21st century has added 'algorithmic thinking' and 'computing literacy' to the repertoire of thinking skills and literacies that have been seen as essential for successful functioning and employment in society (Knuth, 1985; Papert, 1972; Sloan & Halaris, 1985). The proliferation of personal computers and other digital devices in people's everyday lives raised the need for different kinds of skills and literacies, such as 'ICT skills', 'media literacy' and 'digital literacy' (Markauskaite, 2005, 2006). The recent emergence of big data, machine learning, robotics and Al gave the birth to 'data literacy', 'computational thinking', 'AI literacy' and other new skills (Bull, Garofalo, & Hguyen, 2020; Long & Magerko, 2020; Mandinach & Gummer, 2013). Simultaneously, the increasing interconnectivity, complexity, and fast changes in knowledge and skills needed for everyday life and jobs have shifted the attention from technology-centred skills and literacies to a broader set of generic competencies, such as creativity, analytical thinking, active self-driven learning, and global citizenship (World Economic Forum, 2018, 2020).

The current proliferation of AI in workplaces is sparking wild expectations and excitement about a smart, empowered by AI, workforce and the concurrent appearance of low-paid, algorithmically driven,

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unskilled work (Ekbia & Nardi, 2017). Yet, goals about better, more just and inclusive decision-making have been intertwined with concerns about AI governance and exclusion (Ames, 2018; Williamson & Eynon, 2020). The initial fears that machines would replace humans have been followed by the realisation that people are actually already working alongside machines (Nardi, 2017); and there is a need to understand much better how humans could cooperate with AI in ways that contribute to their intelligence and wellbeing (Dafoe et al., 2021). There is little doubt that AI reconfigures the distribution of intelligence, labour and power between humans and machines, and thus new kinds of capabilities are needed (Luengo-Oroz et al., 2020). However, these capabilities are as yet poorly identified and understood.

What kind of capabilities do people need for successful cooperation, functioning, and wellbeing in an interconnected and fast-changing world permeated with AI? How can we conceptualise these capabilities? How can we help learners develop them? How can we empirically study and assess their development?

With this paper, we open a dialogue about the key capabilities people need for work, learning and wellbeing in an AI-saturated world. The aim is to provide a platform for different voices, constructive critique, and joint work, developing a sharper and more inclusive understanding of these capabilities. We adopted a dialogical knowledge-making approach. Our team of 11 co-authors participated in an orchestrated written discussion on rethinking the capabilities for a world with AI. Our team represented different disciplines, conceptual perspectives, career stages and genders. By engaging in semi-independent and semi-joint written polylogue, we aimed to assemble a pool of ideas and engage in constructive critique and collaborative work conceptualising the capabilities needed for a world with AI. Simultaneously, we discussed how learners could be helped to develop these capabilities and what kind of research methods could enable us to test and refine our hypothetical views.

2. Defining the territory

Before starting our polylogue, we need to clarify our terminology. Different terms have been used in the literature to describe what people need to know and be capable of doing to function successfully in society, such as 'literacy', 'skills', 'competencies' and 'capabilities'.

The term 'literacy' historically has been associated with one's ability to read and write. The initial technical notions of literacy as the ability to use the alphabet have been replaced with the functional notions of literacy as the ability to use technical skills to pursue personal goals and function within society. For example, the recent OECD (2019) report on adult skills describes literacy as "the ability to understand, evaluate, use and engage with written texts to participate in society, to achieve one's goals, and to develop one's knowledge and potential" (p. 18). Similar notions of literacy have been applied to conceptualise various technology-related abilities, such as 'ICT literacy' and 'digital literacy' (see for review Markauskaite, 2006). A similar view of literacy is used in the context of AI (Long & Magerko, 2020).

The term 'skills' rather than 'literacy' has become more common recently, particularly in discussions about 'the 21st-century skills' or 'generic skills' and in professional education and lifelong learning contexts (OECD, 2019). This term, however, has been heavily criticised in educational literature. This critique centred on two main aspects. First, the term 'skills' is usually associated with systematic instruction and pre-specified measurable levels of achievement. Thus, it is often too specific to address the unpredictability of what people will need to be capable of doing in the future. Secondly, when this term is used to refer to 'future proof' or '21st-century skills', it usually includes traits or personal characteristics (e.g., creativity) rather than skills (Kirschner & Stoyanov, 2020), and is thus viewed as being semantically inaccurate. Such literature usually proposes a broader term 'competency' as a more appropriate term in future-oriented contexts (cf. Buckingham Shum & Deakin Crick, 2016). Other literature, however, assigns little importance to the differences between these terms. For example, the OECD (2019) report on adult skills mentioned above uses the terms 'skills' and 'competency' synonymously even if it acknowledges that 'competency' is a broader term that includes "knowledge, skills and attitudes (beliefs, dispositions, values)" and refers to "the application and use of knowledge and skills in common life situations as opposed to the mastery of a body of knowledge or a repertoire of techniques" (p. 98).

In more recent times, broader terms such as 'capacity' and 'capability' have been commonly used (Gangas, 2016; Markauskaite & Goodyear, 2017; Poquet & de Laat, 2021). These terms primarily refer to the human qualities and potential to do certain things and achieve desired outcomes. It shifts the focus from the demonstrated behaviours to the potential, dispositions and opportunities within one's reach to pursue specific values and outcomes.

For inclusiveness, we adopted the broader term 'capabilities' rather than 'literacy', 'skills' or 'competency' in this paper. This is in line with our aim to explore the space of what people should be capable of doing to succeed in a world with AI, rather than to provide one specific definition of what capabilities directly related to AI entail. Although it is certainly important to understand the latter capabilities as well, this work has partly been done by others. For example, Long and Magerko (2020), drawing on an extensive scoping literature review, explored the notion of AI literacy. They defined '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" (p. 598). Their review resulted in 17 core competencies related to people's understanding of what AI is, what AI can do, how AI works, how AI should be used, and how people perceive AI. However, the issues induced by AI reach far beyond skills and knowledge or attitudes directly related to AI, to include characteristics and competencies that have been critical for many previous generations but now take on new shapes, such as cooperation, creativity, complex problem-solving, flexibility and change (Buchanan et al., 2018; Markauskaite, 2020). In short, an AI-centred view of capabilities may not capture many other capabilities that learners need to develop for a world with AI.

This inevitably brings the danger of being too broad and answering the question of "What kinds of capabilities are needed for a world with AI" by saying "The same ones as always". Even so, it is important to consider how these capabilities change in an AI context. What is distinctive about AI-based technologies is the ability to automate certain processes and emulate (even exceed in some cases) human performance. It is essential to consider new possibilities and barriers one might encounter in enacting and enhancing those capabilities that now become distributed between humans and intelligent machines when humans and machines perform in cooperation. In this context, we asked the experts to address the above questions about capabilities that people need in a world with AI.

3. Methodology

In this multi-authored paper, we adopted a polychronic and polyphonic research approach, similar to those used for collective knowledge-making in experimental postdigital dialogues (Jandrić et al., 2019; Matusov, Marjanovic-Shane, & Gradovski, 2019). Jandrić et al. (2019), drawing on Peters (2015) work, describe postdigital dialogues as a form of 'collective intelligence':

> "a scientific, technical and political project that aims to make people smarter with computers, instead of trying to make computers smarter than people. So, collective intelligence is neither the opposite of collective stupidity nor the opposite of individual intelligence. It is the opposite of artificial intelligence. It is a way to grow a renewed human/cultural cognitive system by exploiting our increasing computing power and our ubiquitous memory." (Peters, 2015, p. 261 cited in; Jandrić et al., 2019, p. 164).

One may question if the opposition of human and artificial intelligence is necessary. However, given the complexity of the challenge that we set out to explore, and the importance of multiple human perspectives in finding acceptable solutions, this approach was appropriate.

Over about three months, we engaged in an orchestrated written conversation, characterised by a polychronic organisation of our writing, which occurred non-linearly in the form of asynchronous dialogue. The collaborative writing was guided by the polyphonic structure, aiming to ensure that an independent voice of each author representing a particular intellectual tradition is initially heard, and then juxtaposed with other voices and attuned to each other.

Before starting this polylogue, we worked together as a part of a larger multidisciplinary team for about 12 months on creating intellectual foundations for a joint project, "Empowering learners in the age of AI". The first author, who orchestrated the dialogue, invited team members with expertise in different domains to participate in a jointly written polylogue to discuss capabilities that students need for a world with AI. These members, who became co-authors, had backgrounds in diverse disciplinary fields (e.g., education, learning sciences, computer science, and engineering) and represented different conceptual perspectives towards the capabilities and AI in education. They were chosen seeking to ensure representation of different career stages and genders. Each co-author was able to invite their collaborators representing a similar conceptual perspective to participate in the polylogue alongside. One additional co-author joined the team at this stage.

The polylogue took place online using Google Docs for collaborative writing. It spanned three phases.

In Phase 1, each co-author was asked to adopt a perspective representing their domain of expertise and respond to a set of five questions. In their responses, they were asked to articulate their perspective and describe: 1) what kind of capabilities will people need in a world with Al, 2) how these capabilities could be conceptualised, 3) how they could be developed, 4) how this development could be empirically studied and assessed, and 5) what else should be considered when we think about how to prepare people for a world with AI. To ensure that all voices are heard and avoid 'groupthink', each co-author was asked to write their initial contribution independently and not read the contributions of other co-authors before drafting their responses.

At the end of this phase, the first coordinating author integrated all responses to each question and made some editorial comments asking authors to clarify their ideas when necessary. She also identified the initial overarching themes, including the dominant orientation of each perspective, and drafted openers for the joint discussion.

In Phase 2, all authors were invited to 1) read each other's contributions and leave any questions and comments for their co-authors; 2) read peer comments and make changes that they deem necessary in their answers, and 3) reflect on everyone's contributions and add their insights to the joint discussion. All authors were invited to co-write this section by integrating their ideas and critique while respecting each other's points. The first author lightly edited the jointly produced text and submitted it for peer review.

Phase 3 was conducted in response to the reviewers' comments. They recommended that we present our individual contributions continuously, each subsection addressing all questions, informing a more extended comparison of our perspectives. In response to this, we restructured the paper. We made sure all voices were represented in a balanced way and further strengthened the synthesis. During the synthesis, the coordinating author identified distinct features of each perspective and proposed four initial dimensions for comparing them. Two dimensions focussed on the *distribution of agency* 1) between individuals and collectives, and 2) between humans and AI. Two other dimensions concentrated on 3) *the focus of the capabilities* (what these capabilities are for) and 4) *the locus of the capabilities* (where these capabilities are realised). Using these dimensions, she drafted initial synthesising tables and figures. They were discussed with all authors in a meeting and revised several times until consensus among all authors was reached. Each author reviewed and ensured that their perspective was represented accurately in the synthesis.

In the following 'Results' section, we present our individual contributions, moving to the 'Joint discussion' section where we present a synthesis from our joint sensemaking.

To ensure trustworthiness (Korstjens & Moser, 2018), we made our perspectives explicit and the methodological design transparent. We also conducted our polylogue online, leaving a 'thick digital trace' of how our ideas evolved. We are by no means claiming objectivity, exhaustive coverage, or generalisability of our findings. However, like others involved in similar knowledge-making experiments, we can claim that "we are tentatively confident that this article produces more knowledge than the arithmetic sum of its constituent parts" (Jandrić, 2019, p. 180). Given the state of the art in this domain, we hope that our collectively produced knowledge offers a valuable platform for future dialogues and research in this space.

4. Results

Our individual perspectives on the capabilities for an AI-infused world ranged from more individual, cognitively oriented views to more relational, socially oriented perspectives. We use this dimension as a guide to sequence our contributions, starting from the perspectives that emphasise individuals and moving towards broader, relational conceptualisations.

4.1. Using AI to become an agentic learner: A self-regulated learning perspective (Dragan Gašević, DG)

4.1.1. Q1: What kind of capabilities do people need in a world with AI?

Developments in AI accelerate technological change in workplaces and demands for continuous learning, upskilling, and reskilling. To maintain job relevance and support future career transitions in a world with AI, individuals will require highly developed self-regulated learning (SRL) skills (Winne et al., 2017). These are not just important for matters related to labour markets but also for other aspects of life such as personal finances, health, culture, and climate. SRL skills play a critical role in all facets of human learning and development. For instance, SRL underpins how learners navigate and operate on online information, form queries to search information on the Web or social media, and scan and assemble information. At each step, learners decide what information is relevant and judge how it supports achievement of their learning goals (Dunlosky & Thiede, 2013). The need for SRL skills is even more acutely emphasised in the age of AI due to two prominent reasons: (i) the need to adapt (re- or up-skill) frequently due to speed of job and life changes; and (ii) the need to maintain agency in decision making while working AI systems.

4.1.2. Q2: How can we conceptualise these capabilities?

I generally draw on the literature on self-regulated learning (SRL) to conceptualise these capabilities, specifically, the degree to which students exercise control over their thoughts, feelings, and means for attaining learning goals is the core of SRL (Winne, 2011). Key assumptions of SRL theory are learner agency and knowledge construction. Learners choose what to learn and how they will learn, in the context of external goals, resources and constraints (Winne & Hadwin, 1998). They construct knowledge using operations (or learning tools) to interact with information.

In my research on SRL in connection to AI, I focus on the *development of theory-driven AI techniques for analysis of SRL constructs* such as learning strategies, motivation, and time management (Gašević, Dawson, & Siemens, 2015). This research aims to improve instrumentation of learning environments and develop analytic techniques that can offer deep insights about SRL as it unfolds to increase research understanding and inform future interventions.

4.1.3. Q3: How can we help learners develop these capabilities?

When it comes to developing capabilities to learn, effective scaffolding and feedback are essential (Wisniewski, Zierer, & Hattie, 2020). Learners often do not choose effective learning practices such as self-testing and spaced learning (Bjork & Bjork, 2020). These poor choices can be attributed to three reasons (Winne, 2006): learners are unaware of effective learning practices, learners are not aware some learning practices can be used across different tasks, and learners do not have sufficient skills to effectively use some learning practices. Moreover, as agents, learners also make poor judgments of how much they learned, the quality and relevance of information they found, and when and how long they need to study for.

In my research, I aim to develop AI-driven scaffolds that analyse learner activities in real time and offer guidance to the learners in the form of feedback, prompts, and hints (van der Graaf et al., 2020). The reason for this lies in the fact that learners need to receive personalised feedback (from teachers and/or peers) on whether they used effective learning practices. The key challenge is however that personalised feedback requires significant resources that educational systems, schools, and teachers cannot often afford. This is why future work on scaffolding and feedback should go hand-in-hand with work on AI-driven methods in learning analytics for empirical study and developmental assessment of SRL skills (Molenaar, Horvers, & Baker, 2019).

4.1.4. Q4: How can we empirically study and assess the development of these capabilities?

While the use of digital technologies allows for the collection of unprecedented amounts of data, such data are often not sufficient to provide reliable and valid measurement. In my research, I address this issue by using multichannel data such as clickstreams, mouse movements, and eye-tracking (Azevedo & Gašević, 2019), enhanced instrumentation of learning environments such as the use of highlights with specific meaning reflective of motivation, cognitive, and metacognitive factors (Jovanović, Gašević, Pardo, Dawson, & Whitelock-Wainwright, 2019; van der Graaf et al., 2021), and develop analysis methods that combine different AI and data analytic techniques such as deep and machine learning, process mining, and network analysis (Ahmad Uzir, Gašević, Matcha, Jovanović, & Pardo, 2020; Fan, Saint, Singh, Jovanovic, & Gašević, 2021; Saint, Gašević, Matcha, Uzir, & Pardo, 2020). All these developments form a foundation for advancements in understanding SRL skills in the age of AI and inform design and validation of AI systems that promote development of AI skills.

Future research needs to work towards three critical objectives to enable empirical study and development of SRL skills at scale:

1. *Advance unobtrusive data collection techniques* that deepen understanding about SRL as a dynamic process traced in terms of theory-based, intensively sampled, fine-grained, temporally ordered data about learners' activities. This should result in big data which are significantly more comprehensive than currently used in research and practice. Such data will be analysed using AI algorithms and the results of these analyses will be translated into personalised learning analytics that support SRL.
2. *Develop and validate novel automated methods to analyse* information learners access, interact with (e.g., content highlighted) and create (e.g., concepts mentioned in notes) to track progress in learning and developing SRL skills.
3. Formatively evaluate and progressively increase benefits of *AI-based personalised SRL scaffolds* relative to (i) existing approaches to adaptive feedback, (ii) schedules for fading feedback; and (iii) issues affecting uptake.

4.1.5. Q5: What else should we consider?

We need to develop frameworks that reconceptualise SRL to recognise hybrid human-AI regulation that will inform our research and practice of learning and teaching (Holstein, Aleven, & Rummel, 2020; Molenaar et al., 2019). While existing models of SRL recognise the role of external conditions, they do not sufficiently conceptualise the active role AI-based agents may play in regulation of learning in a similar way as the role of other learners is recognised in models of socially shared learning regulation (Järvelä, Miller, Hadwin, & Malmberg, 2018).

4.2. Developing broad intelligence: A hybrid cognitive system perspective (George Siemens, GS)

4.2.1. Q1: What kind of capabilities do people need in a world with AI?

Currently, despite hype, AI is still rudimentary in its contribution to human thought and cognition. While there is significant advancement in narrow or domain specific intelligence—such as recognizing cancer tissue or detecting a cyber-attack—true intelligence remains elusive. As such, the core capabilities that people will need in an AI world fit into four categories:

1. *Interpreting and understanding AI system outputs.* This includes skills to understand the data sources and reliability of AI system outputs, as well as a sensitivity to possible errors. The key goal of using AI is to increase and amplify human knowledge or reduce errors in human performance. Having technical and conceptual skills to assess the outputs of an AI system is critical to understanding what can reliably be done with those outputs.
2. *Integrating AI outputs into human knowledge systems.* When AI produces an output, it needs to be acted on by a human being. Even in instances where decisions are rapidly made by AI at a level that humans cannot perform (such as automated stock market trading or risk detection by security software), humans remain the final agents of action at the aggregate level. Skills to process and methods that support the integration of AI outputs into human systems will enable timely decision making and sensemaking.
3. *Assessing and evaluating ethical implications of AI outputs.* AI contains and produces bias. The data and decisions made with that data can create unfair outputs for different populations. Recognizing where bias and unethical or concerning outputs are generated will become an increasingly important capability.
4. *Elevating human cognitive work to creativity and meaning/sense-making domains.* AI can more rapidly perform routine cognitive tasks in many areas than humans can't. As a result, humans will need to elevate their cognitive work to a domain where AI is less capable. Knowledge practices, such as sense making and meaning making will grow in importance. Similarly, creative actions, such as brainstorming and divergent thinking will become more important capabilities.

4.2.2. Q2: How can we conceptualise these capabilities?

My interest is primarily in understanding the intersections between human and artificial cognition. As a result, the focus is on what happens when an artificially produced knowledge output (e.g., risk assessment, automated search, or social media trends created by categorizing abundance of information) enters the human knowledge system. The human knowledge system can be defined as any type of knowledge work that humans do and where they are the final arbiter. This could include a radiologist assessing the outputs of automated medical image analysis, a military officer reviewing the outputs of a threat detection algorithm, or a teacher assessing student risk of drop out models. When the output from AI intersects with human knowledge work, existing literature from HCI and cognitive psychology (notably on decision making) provides some conceptual models. Unfortunately, those models are not focused on granular or specific cognitive activities. In order to assess who should be capable of doing what (human or AI) a conceptual model is required that evaluates which specific cognitive tasks should be performed by which agent under which circumstances. Specific cognitive tasks are the foundation for assessing human and AI interaction.

4.2.3. Q3: How can we help learners develop these capabilities?

The current emphasis on learning as a form of information acquisition will need to give way to more complex ways of creating knowledge. Developing skills to succeed in an AI world requires authentic activities such as problem solving, problem based learning, or similar knowledge work where creation, rather than consumption or duplication of knowledge, are critical.

Additionally, when humans team with AI, the experience of working with a non-human agent will require coordination. For example, in a team meeting, an AI agent could be tasked with actively searching for background information based on existing conversation. This information could include a summary of academic literature, previous comparable projects done within the company, or open web searches. An agent could also provide summaries of conversations during the meeting and this in turn could help to improve idea development. This process—active engagement with AI in routine knowledge work—is likely the best way for learners to develop the coordinating abilities required to engage with AI.

4.2.4. Q4: How can we empirically study and assess the development of these capabilities?

Numerous government agencies, including OECD and national governments in Singapore and Australia, are exploring how to assess 'non-cognitive' skills (Joksimovic, Siemens, Wang, San Pedro, & Way, 2020; Kautz, Heckman, Diris, ter Weel, & Borghans, 2014). These include attributes such as critical thinking, complex problem solving, social and emotional learning. As these are integrated constructs that rely on multiple cognitive functions such as planning, monitoring, idea generation, and critical thinking, assessment is more challenging than traditional approaches where measurement is focused on information acquired or knowledge gained (e.g., when learning a new concept). I am not convinced that many of our existing methodologies and research approaches are able to accurately assess these types of integrated constructs. Researchers will need to draw on complexity science and modelling research methods in order to empirically evaluate the study and development of these skills (Deakin Crick, 2017).

4.2.5. Q5: What else should we consider?

There are things that we do not understand about consciousness in humans. The view that we may at some point have conscious machines seems like a premature declaration. From the stance of 2022, we are still mystified as to the biological basis of consciousness. A provocative statement about 'sentient machines' plays well for press and social media attention. The reality, at least in the short term, is that more pragmatic and practical work will be done in narrow artificial intelligence – namely, AI that focuses on a single task within one domain that does not transfer well to other domains. One concern I have, however, relates to how systematized growing aspects of modern life are becoming. Systems create routine. And routines can be automated. There is a real possibility that as more of our lives become structured that we will end up meeting AI halfway, having optimized all aspects of our lives to some utilitarian goal.

4.3. Fostering human creativity: A '4Cs' perspective (Rebecca Marrone, RM)

4.3.1. Q1: What kind of capabilities do people need in a world with AI?

Creativity is a core 21st-century skill, taught in various education systems (Patston, Kaufman, Cropley, & Marrone, 2021), and we will need to continue fostering it. Creativity is defined as a novel and effective way to solve a problem (Plucker, Beghetto, & Dow, 2004). In isolation, machines can be more effective problem solvers than humans, and they can exhibit novelty. But novelty or effectiveness alone is not creativity. The challenge to being creative is exhibiting novelty, effectiveness and contextual sensitivity simultaneously. For example, within the realm of automated creativity, machines are able to reproduce art and poetry that is in fact novel. However, creativity also depends on contextual factors such as the environment, social norms, and the historical milieu in which we are situated. Humans naturally are attuned to these social factors more than machines, and in many areas of our lives it remains uniquely human to be creative.

Additionally, creativity is essential for human development and this kind of creativity is deeply personal and situated. Take a 5-year-old who is learning to tie their shoes. The child may figure out and learn a new and effective technique, and, at that moment, they are exhibiting creativity. However, to the 6-year-old who has been tying their shoes using the same method for 12 months, there is no longer creativity. Creative AI cannot replace this kind of human creativity as its value is extremely personal.

4.3.2. Q2: How can we conceptualise these capabilities?

I look at creativity in a world with AI through a 4C model: mini c, little c, Pro C and Big C (Kaufman & Beghetto, 2009). ***Mini c*** or 'personal creativity' represents the personal (Runco, 1996; Vygotsky, 2004) and developmental (Cohen, 1989) aspects of creativity. Mini c is concerned with subjective self-discoveries that are important to the person involved, even if other people do not recognise the activity as being creative. An example is the 5-year-old learning to tie their shoes as mentioned above. *Little c* is also termed 'everyday creativity' and refers to something that other people recognise as creative. Examples of little c creativity include designing a new way to teach statistics and then writing lesson plans to share with other teachers. *Pro C* or 'professional creativity' involves the deliberate practice of becoming an expert in any field or discipline. *Big C* or 'legendary creativity' is the culmination of genius work, in that this work will be appreciated and remembered for centuries.

AI can support creativity, particularly Pro C and potentially Big C, as it can extend an expert's knowledge. Yet, it does not replace mini c or little c creativity. At the mini c and little c levels, the creative output is not as important as the self-discovery that occurs through the creative process. It is therefore important to develop both an appreciation and understanding of when and where AI is most useful.

4.3.3. Q3: How can we help learners develop these capabilities?

We can help individuals learn to be more creative by presenting problems in new ways and creating environments that enable them to try new ways of solving these problems. AI can help us extend our creative thinking when we are 'experts' in a domain as it can trial or test things that may not be as readily possible in real life (Kaufman & Beghetto, 2009). For example, AI could enable an astrophysicist to develop their understanding of black holes without requiring humans to venture towards them.

However, in educational context, mini c and little c creativity are also very important as they play critical roles in human development, and allow students to experience a sense of achievement and self-worth (Kaufman & Beghetto, 2009). For example, learning a new way to write your essay in Grade 8 is rewarding at both the individual and societal level. AI can certainly be used also to encourage and scaffold this kind of creativity.

4.3.4. Q4: How can we empirically study and assess the development of these capabilities?

Researchers in learning analytics/AI are trying to empirically assess creativity through log data, however, currently, only a tiny aspect of creativity (e.g., divergent thinking) is measured in this manner (Gal, Hershkovitz, Morán, Guenaga, & Garaizar, 2017). Other elements of creativity, such as the creative product, also need to be measured and scored. Various individual and contextual factors, such as personal characteristics and environment, also need to be assessed and considered. From this perspective, machine learning techniques alone may not assess creativity reliably and effectively; and the human in the loop is crucial. Researchers therefore should aim to develop machine learning techniques and AI tools that help people assess and empirically study creativity rather than leave assessment of creativity for AI tools alone.

4.3.5. Q5: What else should we consider?

To successfully integrate AI into our lives we need to understand that both machines and humans can contribute to creative outcomes at different times and differently, and we need to understand that there is a time and a place for both. To summarise, I pose and answer these questions. Can AI be creative? Yes. Does AI need to develop a new way to tie shoes to support 5-year-olds? Probably not. Can AI assist or help the 5-year-old learn new techniques? Yes. Working together with AI as a 'teammate' is where AI will support creativity. AI will never replace human creativity, but it can extend it to new frontiers and support its development.

4.4. Empowering people to make free choices about AI: Sen's capability perspective (Oleksandra Poquet, SP)

4.4.1. Q1: What kind of capabilities do people need in a world with AI?

Integrating AI tools into daily practices requires that people become deliberate about their use of digital tools. Cultivating deliberate engagement was argued for by Salomon, Perkins, and Globerson (1991) who differentiated between two effects that intelligent technologies have on human cognition: 'effects with' and 'effects of'. 'Effects with' impact the outcome of the task shared between a human and a machine. For instance, an autocorrect impacts task efficiency as one can write faster. In contrast, 'effects of' refer to the cognitive residue that a task performed with technology has on the human mind. Namely, constant automation of writing might result in lack of authenticity or forgetting spelling. Both 'effects with' and 'effects of' may negatively impact human cognition, hence requiring that individuals mindfully engage with digital tools (Salomon et al., 1991). To engage mindfully demands that individuals understand how AI technology operates. Notably, this technical knowledge is inseparable from the availability of systemic freedom: people need to have the choice between 'effects of' or 'effects with' to achieve what they value at a given moment.

4.4.2. Q2: How can we conceptualise these capabilities?

I think of human capabilities in a world with AI through Amartya Sen's capability perspective (Sen, 1985). This philosophical view focuses on the values that individuals can freely choose, and structural constraints that hinder achievement of what is valued by individuals. Capability centers on 'agency', 'what a person is free to do and achieve in pursuit of whatever goals and values he or she regards as important' (Sen, 1985, p. 203). The lack of freedom of choice by an individual, captured by Sen through the so-called 'conversion factors', can be systemic, therefore, Sen's capability conceptually describes both individuals and systems they are a part of.

Applied to the capabilities in the world of AI, this perspective requires that individuals understand how AI-based technology can alter their activity, i.e., the 'effects of' and 'effects with' AI on cognition, exposure to information, amplified participation, etc. From there, individuals need to be free to choose between 'effects of' or 'effects with'. Such a choice is not necessarily present within the human capital approach to learning, which dominates political discourse today. A human capital approach focuses on skill development as an economic investment, not on the availability of choice or systemic opportunities to choose what 'effects of' AI humans are comfortable with. Hence, the human capital perspective may privilege 'effects with AI' because automation can enable a faster outcome which promises a short-term return on investment to the employer.

4.4.3. Q3: How can we help learners develop these capabilities?

Sen advocated for the support of choices to achieve what an individual values. In a contemporary context, that requires an additional skill: being able to resolve tensions between individual and collective values which may be in conflict. Awareness of one's own values and the possible detrimental effect of individual actions amplified by AI is needed to support human capability development. I explain this drawing on a study by Lee, Yang, Inchoco, Jones, and Satyanarayan (2021). The authors describe how individuals skilled in scientific thinking and data literacy contribute to the spread of false beliefs amplified by AI within informational eco-systems on social media. Individual skills such as scientific thinking, work with direct sources, and ability to interrogate data as a part of data literacy, were not sufficient to tackle collective misinformation. Algorithm-driven social media supported individual freedoms to act (which in Sen's view is exercising one's freedom), and AI supported the acceleration of collective sense-making and knowledge building. Except here, the collective sense-making was flawed as data literacy was used to further support one's identity rather than scientific progress.

To avoid such a scenario, human capability to question one's own identity and values as a larger prism that governs one's actions and decisions should also come into focus. Given the diversity of human values and choices, the need for certain principles or collective goals accepted by most is needed to navigate tensions between individual and collective values. The focus on education and lifelong learning for democratic citizenship towards equity, sustainability, or valuing human life above all can become such principles. Focus on humanistic values and sustainability can be an essential part of the curriculum in the world where AI-based technologies have potential to magnify individual actions and skew collective patterns towards unexpected emergent processes.

4.4.4. Q4: How can we empirically study and assess the development of these capabilities?

Capabilities that support deliberate engagement with AI, making choices, navigating individual and collective values are rooted in scientific understanding of developing agency, identity, and the role of context. Agency, identity and context need to be studied more deeply and through an intersection of quantitative and qualitative methods, in ways that span different scales and dimensions of learning from a systems point of view. From the empirical point of view, analysis of learner change at multiple levels as a dynamic process can explain learner development trajectories and inform how technologies can augment and support them (Poquet et al., 2021).

4.4.5. Q5: What else should we consider?

I think humanities are critical to developing capability and human development through learning. Historical thinking can help position events within contexts, as well as provide a larger understanding of the evolution of tools and their roles in human activity and development. Evolutionary thinking, literature, arts, and philosophy can foster empathy and understanding of the diversity of contexts, enabling a more empathetic view of the values of others and respect towards them. Thus, the technical and scientific focus, characteristic of contemporary educational discourse, can benefit from being placed in a broader set of humanistic values, within and beyond educational settings.

4.5. Creating AI for human values: A human-centred AI perspective (Roberto Martinez-Maldonado, RMM)

4.5.1. Q1: What kind of capabilities do people need in a world with AI?

People will need capabilities related to design, ethics and philosophy. Overall, identifying the capabilities that people will need in an AI world requires a deep understanding of the capabilities that intelligent software will feature in the short and mid-term in the different sectors of our society. Unfortunately, this is a very hard task. No-one really knows how fast AI will develop and to what extent it will impact each of such sectors. The only certainty is that people will need to reinvent themselves in faster cycles in the foreseeable future as a direct impact of AI on the workforce, which we are already experiencing especially for routine tasks (Nabi, 2019).

Therefore, those capabilities related to design, ethics and philosophy will be critical for creating AI for human values. Design thinking and design skills will enable humans to decide the degree of human control and computer automation for solving key human challenges. Helping people to develop ethical and philosophical thinking from early stages of education, will enable the future designers and developers of AI to create innovations that keep the human values at the centre. A strong philosophical stance will also enable humans to explore the realms of human consciousness more deeply and move beyond an algorithmic view of ourselves.

4.5.2. Q2: How can we conceptualise these capabilities?

I look at the capabilities from a human-centred design perspective. In the same way as we assume that AI will impact the relevance of some of our human capabilities, it is necessary to also re-think how our human capabilities can shape the materialisation of AI innovations. From an ergonomics perspective, the theory of instrumental genesis describes two mutual processes that explain the co-evolution of humans and artefacts we interact with (Rabardel & Beguin, 2005). When we appropriate a new artefact, we generate a mental schema that enables us to use it to perform some task. Assuming people will interact with AI at some point, this first process, known as instrumentation, will require the careful identification of the relevant capabilities of the human that would be required. This is about changing 'ourselves'. However, the second process, instrumentalisation, is about making changes in the artefact or tool itself to fit the purpose of humans. This means there is space for designing AI and adapting the AI not only to the task itself but to the way in which the AI products will be used by people. From this design perspective, we need to think about the capabilities of humans facing AI and also about the capabilities of the people to design AI in ways that can effectively fit the context of human activity. This theoretical perspective is known as Human-Centred AI (Oppermann, Boden, Hofmann, Prinz, & Decker, 2019). Although this approach is in its infancy, it aims to combine research on AI algorithms with user experience and design methods to shape technologies that ethically augment, empower, and enhance human performance.

4.5.3. Q3: How can we help learners develop these capabilities?

The capabilities for human-centred AI need explicit attention. Human-centred design, ethics and philosophy are commonly not extensively taught in K-12 or university curricula, and there is a particular absence of these topics in engineering and computer science degrees (Fiesler, Garrett, & Beard, 2020). This is a threat to the development of ethical AI. Schön (1983) explained how practitioners (such as engineers and designers) have their own 'knowledge codes' interwoven into their practices. Ethical and philosophical thinking should be a part of these codes as these practitioners are designing AI systems that will end up making important decisions that can impact the lives of other people. A great number of potential problems with future AI developments can be prevented by educating students today to imbue the future development and uses of AI with critical human values. In addition, design is a critical subject matter for developing learners' design capabilities and for fostering human-centred AI through their hands-on design practices.

4.5.4. Q4: How can we empirically study and assess the development of these capabilities?

There are already established approaches to study and assess the development of different component capabilities that I mentioned, such as design skills, ethics and philosophy. But a critical question is: how to assess these in the context of the design of AI and associated practices? Since AI is a rapidly evolving field, it is very challenging for educators to keep track of all the current innovations and potential design and ethical implications of new developments. A potential way to address this is to refer to authentic assessment practices (Gulikers, Bastiaens, & Kirschner, 2004). Authentic assessment focuses on students applying knowledge and skills in high-fidelity, real-life contexts. Students would then be required to demonstrate relevant competencies through a significant and meaningful accomplishment of tasks. For example, human-centred AI aspirations, such as creating reliable, safe and trustworthy AI (Shneiderman, 2021), and their transfer to other situations could be the focus of the assessment.

4.5.5. Q5: What else should we consider?

In order to create human-centred AI we need to adopt human-centred practices at various levels (e.g., human-centred policy, human-centred computer science curriculum). In fact, inroads are being made to create human-centred learning analytics (Buckingham Shum, Ferguson, & Martinez-Maldonado, 2019). This is creating value-sensitive AI to scale up the support provided to students by giving an active voice to different educational stakeholders in the design of such data-intensive innovations (Carvalho, Martinez-Maldonado, Tsai, Markauskaite, & de Laat, 2022).

4.6. Seeing self and AI in a larger system: A social realist perspective (Sarah Howard and Jo Tondeur, SH/JT)

4.6.1. Q1: What kind of capabilities do people need in a world with AI?

Differently from others, we consider capabilities needed in an 'AI world' from the position of the teacher, but our argument could be extended to other professions. What are the competencies teachers need to function in an AI world and to prepare their students for an AI world? We argue that there are two important points to consider when thinking about digital competencies in relation to creating learning experiences and teaching opportunities that take advantage of AI (for an overview see Zhai et al., 2021).

The first capability is related to the individual. There is one certainty in digital technologies—that they will continue to change. When considering an 'AI world', it will most definitely be a world that is not static and one where new technologies are continually emerging. Therefore, a key capability of teachers will be to critically engage with new technologies and consider them in relation to learning experiences and their own teacher work (cf. JISC, 2019). This requires teachers to have some level of data literacy, specifically how to make decisions about which tools to use and for what purposes.

The second capability sits with institutions since teachers' capabilities in this field are inextricably tied to the digital tools and infrastructure they are expected to use. Educational institutions will also need to have vision and leadership to help shape how they as a group engage with AI and the expected learning. Specifically, this means providing the necessary support to engage with AI-enabled digital technologies and data. Therefore, a further capability will be institutions' data infrastructure and support capabilities to enable teachers to trial and experiment with new digital tools in real learning environments (cf. JISC, 2020). This provides teachers with a framework, but also can guide the type of support available to them to engage with new digital technologies.

4.6.2. Q2: How can we conceptualise these capabilities?

We consider human capabilities for a world with AI from a social realist perspective, meaning that the use of AI and other digital technologies is not completely relative to the individual. We can think about the nature of capabilities from the position of affordances of digital tools and how these tools support teachers' work and learning; but they are also guided by social and cultural expectations for use of digital technologies.

Digital tools have properties and affordances that are real, which means they are distinct and independent (Bower, 2017). Therefore, they have certain affordances and limitations affecting how they can be used. Further, the nature of teachers' capabilities to integrate new digital technologies can be conceptualised in relation to what type of learning is expected or desired. This is not necessarily decided by the teacher. Teachers have some level of autonomy in a given field, such as a discipline or type of educational institution. However, their work is defined by the basis of achievement in that given field, such as assessments, developing dispositions and the 'desired learner'. Teachers' capabilities will comprise being able to support learning to meet these standards through digital technologies. Therefore, teacher capabilities are a trade-off between what learning or work is possible with a given digital technology, and what learning or work is expected of the teacher in their given field.

4.6.3. Q3: How can we help learners develop these capabilities?

Both teachers' developing competencies to use digital tools and their institution's ability to support this work, are key considerations in developing teachers' capabilities. Given that teachers' capabilities need to be reflective of expected learning, these expectations become possible to target and address when part of a clear institutional vision (Tahiru, 2021). This also means developing these capabilities is more likely to be an institutional priority, where infrastructure and support are available to teachers as they engage in professional learning to build competency.

In terms of an 'AI world', a key component of this development will be making AI visible and creating opportunities for teachers to gain experience using AI-enabled tools, to better understand their affordances for learning, and to build confidence, critical engagement and literacy. One approach to this is to include teachers in discussions about how to use data and visualizations from an analytics dashboard, to support their learning and teaching (Gray, Schalk, Rooney, & Lang, 2021).

4.6.4. Q4: How can we empirically study and assess the development of these capabilities?

Assessment of developing capabilities needs to be sustainable and reflective, so it can itself contribute to ongoing development and refinement of practice (Howard, Schrum, Voogt, & Sligte, 2021). This needs to be an ongoing process, because of the constantly changing nature of digital technologies— in particular AI-enabled tools (Tahiru, 2021). We argue that participatory action research and design-based research are two approaches that can support empirical study of developing competencies and build teacher capacity and competencies with digital technologies (Markauskaite & Reimann, 2008). The development of competencies needs to be situated in teachers' contexts, and relative to their students' and institutional needs. Therefore, to measure their development it needs to be embedded in practice and measurable against meaningful benchmarks, co-designed by teachers and stakeholders.

4.6.5. Q5: What else should we consider?

In terms of teachers, the aim of considering competencies, now and in 15 years, is to focus on the possible learning experiences available through use of a digital tool—rather than focusing on the tool itself. The question is then, what do teachers need to know to use digital tools well and for their desired purposes? The second point is that capabilities, what teachers need to know to support learning, do not exist in isolation. They are embedded in school and educational systems, dictated by curriculum and social expectations. The wider system is an important component when considering how capabilities will change and evolve over time and in response to changes in digital technologies.

4.7. Navigating AI-mediated world views: an AI-mediated discourse perspective (Simon Knight, SK)

4.7.1. Q1: What kind of capabilities do people need in a world with AI?

For a society in which people can make sustainable personal, professional and civic decisions, people must be able to understand multiple perspectives, to evaluate evidence, navigate uncertainty, think divergently or creatively, and understand their own position in relation to others. The ability to navigate one's own and others' views, and to shape and reshape these, is fundamental to this.

AI raises distinctive challenges in this regard, in the way that it may be used to limit and frame human interactions. Specifically, there are concerns where technologies may be used to, among other things:

- remove human judgement and growth in decision making by reifying existing systems into algorithmic, opaque 'black box' decision tools;
- both hide differences in opinion, and over-emphasise extreme views; and
- falsely represent and target human action through, for example, deep fakes and highly targeted political advertising in which the intent is to mislead based on demographic group, rather than communicate intended policy or rationales.

In considering how AI capabilities are instantiated through policy, including in curriculum debates, we should avoid only instrumental goals aiming, for example, for direct economic ends. Instead, we should focus on capabilities (and learning) to allow learners to understand the world around them—including the role of AI in it—but also to understand their role in reshaping that world; learners, technologies, and society are intertwined or mutually constitutive in this regard. The skills and knowledge developed around coding, data literacy, understanding how algorithms and other technologies work, are all crucial not just for workforce participation, but for civic participation. This civic participation is still underpinned by people's capabilities to evaluate and engage with each other's and one's own ideas.

4.7.2. Q2: How can we conceptualise these capabilities?

Sociocultural approaches to learning bring a particular focus on the negotiation and tool-mediated development of understanding of knowledge (Knight & Littleton, 2017). AI-grounded tools afford particular opportunities, and imperatives, for dialogic learning. Human capacities for engaging with ideas, making judgements, and creativity will be ever more important in an AI world (the imperative). In parallel, AI also affords opportunities to create tools to foster effective collaboration, support exposure to divergent ideas, and create and re-create cultural tools through their digital affordances (Knight, 2020).

Indeed, mediation is precisely a feature of AI that marks it out as interesting; the potential to reorient the ways in which we interact with our work and with each other through tools. For example, this might include algorithmic tools that support connected stakeholders, easing access to and translation of evidence and ideas, and prompting at critical argument junctures. Of concern is the systemic capabilities required to ensure, for example, the regulation of AI technologies, the use of AI to augment and enrich rather than define and constrain our capabilities as knowers, or capabilities that foster and enrich democratic participation. AI provides a set of affordances for tool development (of a range of kinds), that may shape individual and social processes, just as these shape such tool development. It is impossible to consider capabilities for an AI world, without considering the capabilities of AI and the ways we may shape, be shaped, and reshape these capabilities.

4.7.3. Q3: How can we help learners develop these capabilities?

In considering how to develop capabilities in an emerging context, it is important not to discard well-grounded existing practices, to recognise emerging tool-mediated practices, and to not fall into deterministic narratives of the impacts of technology (Oliver, 2011). Nevertheless, here I will focus on the distinctive features of AI to help learners develop needed capabilities through dialogic learning. AI raises new learning needs and affords new opportunities for dialogic learning, building on the body of work on computer-supported collaborative learning (Wise, Knight, & Buckingham Shum, 2021), artificial intelligence in education (Grandbastien, Luckin, Mizoguchi, & Aleven, 2016), and other technologies including the internet (Knight & Littleton, 2015b; Wegerif, 2012). For example, these opportunities include dialogic agents that act as 'chat bots' in individual and small group activity, tools that create effective group work contexts, tools to embed disciplinary and professional contexts and guide learners through materials with interactive support, and so on. The tools of AI may be used to develop the capabilities needed for an AI world through engaging people in dialogue, supporting them to connect their existing knowledge to new areas, and fostering problem solving and collaboration through tool-mediated group-formation and artefact creation.

4.7.4. Q4: How can we empirically study and assess the development of these capabilities?

We should embrace AI tools in our assessment practices of different capabilities, including those needed to participate in AI-mediated dialogues. However, the effective use of AI is underpinned by our system-wide capabilities to design, deploy, and improve these tools. This is best illustrated through an example: AI with the ability to identify a variety of classroom dialogue—exploratory, or accountable talk—known to be associated with learning (Clarke, Resnick, & Rose, 2018; Knight & Littleton, 2015a). The tool can be implemented to identify individual speakers in a classroom, and correctly classify instances of different kinds of dialogue across the variety of interactions that take place.

How should such a tool be used? It is crucial to our interactions in an AI world that we have the capabilities to vary this use, for example where appropriate to support: individual and small groups of learners, through direct feedback to them; teachers, through feedback to them both regarding their classes, and their own practices; and schools, in helping them to implement targeted school improvement plans.

4.7.5. Q5: What else should we consider?

The question of how we prepare people for an AI world is fundamentally a question of values. These are values around the kinds of tool-mediated learning we prioritise (Heersmink & Knight, 2018), alongside those of democratic participation—and the capabilities that underpin this—in our interaction with tools. While governance and policy provide useful tools in themselves, building capabilities to navigate dilemmas in tool use is also key (Kitto & Knight, 2019).

4.8. Representational literacy for collective sensemaking (Simon Buckingham Shum, SBS)

4.8.1. Q1: What kind of capabilities do people need in a world with AI?

One approach to this question is to focus on those capabilities that machines are highly unlikely to be able to do in the near future, if at all, that are important for human development, fulfilment, and employment. This is of course hardly a new proposal. Cognitive ergonomics has decades of established work on the 'allocation of function' within human-computer systems, whereby humans and machines perform those tasks for which they are best suited for overall system performance, but with particular attention to how the human can be brought effectively back into the otherwise automated control loop at critical moments (Feigh & Pritchett, 2014). Turning specifically to educational contexts, Luckin (2018) has argued eloquently that there is little point in teaching people to do what machines can already do as well as, if not better than, humans.

I will focus here on one capability that has been the object of study for several years, namely, the ability to use visual representations to facilitate collective sensemaking, especially when confronted by *wicked problems* (Rittel, 1972/1984), which resist the structuring and formalization required for computational modelling. At the heart of tackling such problems is (i) agreeing on the nature of the problem, (ii) and what might count as a solution, (iii) all the while sustaining engagement from stakeholders such that there is a sense of ownership of the outcome. In this contribution, I introduce work on understanding *participatory representational practice,* that is, the specific set of capabilities that assist such deliberation, drawing on multiple intelligences that machines are far from displaying. As such, it is a strong candidate for capacity building in the age of AI. This is a high-level competency that is needed more urgently than ever in society, which can be learnt. Schools, universities and workplaces typically train us to read and write as solo authors and speakers, paying too little attention to *thinking with visualisations*, and enabling *collective thinking.* I propose therefore, that learning how to assist 'collective ideation' using representational tools is an important literacy for our times.

4.8.2. Q2: How can we conceptualise these capabilities?

Our work has studied the practice by which one can foster, sustain, or restore participant engagement with visualisations in the service of collective sensemaking. Our approach to developing this competency has resulted in the practice of "Knowledge Art" (Selvin & Buckingham Shum, 2014). In the framework, productive participatory visualisation is accomplished by assisting participants to build a collective picture of the challenge they face, and potential solutions. Knowledge artistry is a combination of five key capabilities: *aesthetics* (the choices we make for shaping a visualisation – what's foregrounded, excluded, how polished, how editable); *ethics* (how our moves affect the other stakeholders: recognise/ignore their contribution, change meaning, shift topic); *narrative* (the context for a session: spoken/unspoken expectations of why we're here, how we should proceed, what kinds of meanings will be made, or outputs produced); *sensemaking* (how we interpret unexpected events or anomalies); and *improvisation* (how well we make spontaneous, unplanned moves with the visualisation when breakdowns occur). Fluent knowledge artistry is not a capability that machines can perform, since they draw on a complex mix of different intelligences (cf. Gardner, 2009) including interpersonal, ethical and emotional intelligences that will remain—for the foreseeable future—distinctively human.

4.8.3. Q3: How can we help learners develop these capabilities?

In his pioneering work, Engelbart (1963) emphasised that both humans and machines needed to co-evolve to create human-computer systems that augment intelligence. He argued for "*HLAMT: Humans using Language, Artefacts, and Methodology in which they are Trained*". As with any advanced instrument, competent performance takes practice, but some reach virtuoso level. The proposition then, is that the ability to use interactive visualisations in ways that invite the construction of a shared narrative with stakeholders in the room (physical or online) can be learnt, practised and improved. Teaching this in a data science Masters program has shown that postgraduates can understand the approach, and can begin to reflectively practice the key capabilities: it is possible to develop authentic tasks, coach performance, assess and give feedback (Buckingham Shum, 2019). This is an encouraging sign that this merits further investigation.

4.8.4. Q4: How can we empirically study and assess the development of these capabilities?

Mixed methods combining video analysis of facilitated meetings, artefact analysis of the representations created, and quantitative analysis of the distribution of practitioner actions in meetings, provided the empirical basis that led to the key dimensions of the framework of knowledge artistry (Selvin, Buckingham Shum, & Aakhus, 2010). Using these methods, we also were able to differentiate beginners from experts, and to offer coaching on specific skills (Buckingham Shum, 2019).

4.8.5. Q5: What else should we consider?

The rapid mainstreaming of AI introduces new twists to this practice. Firstly, we must become more fluent in judging if/when to bring AI agents into the conversation to help move deliberations forward. Secondly, the visual representations we use to express ideas are increasingly interpretable computationally. Intelligent agents can now become part of the conversation, even contributing their own issues, ideas and arguments (e.g., Buckingham Shum, Sierhuis, Park, & Brown, 2010).

In our synthesis section, we reframe personal learning capabilities in the context of the threats to democratic society posed by the social media powered breakdown of civic discourse. A promising development which connects such capabilities to the need to rebuild trust in democratic processes, are 'deliberative democracy' models and facilitation processes (Bächtiger, Dryzek, Mansbridge, & Warren, 2018), in combination with participation platforms using interfaces and algorithms designed to promote high quality discourse. We are learning how to design the human/computational capabilities needed to bring large numbers of citizens together to deliberate productively (e.g., Iandoli, Quinto, De Liddo, & Buckingham Shum, 2016; Ullmann, De Liddo, & Bachler, 2019; Zhang, Davies, & Przybylska, 2021), or to engage in evidence-based collaborative problem solving (van Gelder et al., 2020).

4.9. Learning and creating value in networks of humans and non-humans: A networked learning perspective (Maarten De Laat, MDL)

4.9.1. Q1: What kind of capabilities do people need in a world with AI?

Professionals need capabilities to learn in the networks of humans and non-human intelligent systems. Increased digitalization, combined with advancement in learning analytics and AI opens the possibility for designing automated real-time feedback systems capable of just-in-time, just-in-place support for learning, complex problem solving and decision making (De Laat, Joksimovic, & Ifenthaler, 2020). These systems can augment learning and professional development in situ and can impact human and machine collaboration during teamwork (Seeber et al., 2020). Networked learning takes a relational view on learning; and AI systems introduce a myriad of new actors and connections in these networks (Thompson & Graham, 2020). The way human-machine relationships are formed in professional networks impact their capability to learn and solve problems.

4.9.2. Q2: How can we conceptualise these capabilities?

I conceptualise capabilities from the networked learning perspective. Networked learning is a research domain dedicated to understanding how people develop and maintain a 'web' of relations that can be used for learning and value creation (Wenger, Trayner, & De Laat, 2011). As a definition "networked learning involves processes of collaborative, co-operative and collective inquiry, knowledge creation and knowledgeable action, underpinned by trusted relationships, motivated by a sense of challenge and enabled by convivial technologies" (NLEC, 2021, p. 319). What is special about networked learning research is its attention to relationships, attention to technology-mediated activity and collaborative engagement in valued activity. Using a networked learning perspective to conceptualise human-machine learning would mean looking into:

1. *How humans will accept and engage in hybrid relationships with AI* or intelligent machines to advance learning. This opens up questions on the importance of these relationships and how this is influenced by issues such as trust, power, identity, belonging, difference, affection, reciprocity, solidarity, commitment and time (NLEC, 2021). Until recently we have been quite comfortable asking these questions about human-human learning relationships, but with the introduction of AI we need to expand our notion of what is defined as a social practice in which learning interactions take place. In contexts where this practice is no longer exclusively human, it may not be clear with whom/what one is interacting.
2. *How technologies shape and are shaped by activity* (NLEC, 2021). Here, the recognition that tools, artefacts and infrastructure are configured in complex ways and sometimes obscured ways, probes us to ask questions about affordances of technologies, access and appropriation, ownership and control as well as how the social and material are intertwined.
3. *How is collaborative inquiry and joint action in the face of shared challenges achieved?* What does joint knowledge construction mean in a context of hybrid networks? How did the AI systems develop as a consequence of taking part in complex problem-solving processes? Networked learning research in the context of human-machine networks will address how meaning-making, negotiation, participation, sharing, learning, and doing is evidenced in such collaborative practices and how this plays out at scale and over time (NLEC, 2021).

These three aspects will always be addressed in relation to one another to understand how they are intertwined in action and practice.

4.9.3. Q3: How can we help learners develop these capabilities?

When it comes to the development of the capabilities, the value creation framework (Wenger et al., 2011) could provide some inspiration. This framework identifies five kinds of values experienced by the participants by learning in the network: (i) immediate value, such as enjoying learning, (ii) potential value that results in learning that could be potentially applied in future situations, (iii) applied value that results in changes in practice; (iv) realised value that results in understanding how one's performance has been improved, and (v) reframing value that results in transformation of how people define and assess success.

As networks and communities develop, they have stories to tell, and it is in the context of these stories that one can appreciate what learning is taking place and what value is being created. The value creation framework provides a storytelling structure to help learners articulate how human-machine interactions helped them to achieve their goals and changed their practice.

4.9.4. Q4: How can we empirically study and assess the development of these capabilities?

The value creation framework (Wenger et al., 2011) provides a number of indicators associated with the value creation cycles that learners can use to draw upon when telling their stories. Examples of indicators are: level of participation and engagement, quality of interactions, skills acquired, quality of output, reuse of products, innovation of practice, personal performance, reputation, new frameworks or procedures for doing things, etc. Collecting data associated with these indicators is therefore an important way to evidence the value that is being created. With the increased digitalization value creation stories can tap into a great deal of digital data to help articulate how hybrid networked practices facilitated learning processes with the aim to create value. Networked interactions and structures can be visualised to gain an understanding of impact certain contributions and positions in a network may have. Bringing out a shift in focus and content can help to articulate what has been achieved and how it has impacted a change in practice or a way of seeing things. Further, data traces can also help to demonstrate a growth in reputation by tracking how certain outcomes have been reused by other networks and practices.

4.9.5. Q5: What else should we consider?

From a networked learning perspective, the key challenge is to become conscious about how the interplay of relationships mediated by technologies influence our collective engagement in learning processes to create value: (i) How humans engage in hybrid relationships with AI; (ii) How technologies shape and are shaped by activity; and (iii) How collaborative inquiry and joint action are achieved in the face of shared challenges. Understanding how these three elements are intertwined and play their part in shaping human-machine practices will help develop and design policies, structures and architectures to facilitate human learning and value creation.

5. Joint discussion

5.1. Synthesis

Our polylogue shows that the capabilities for a world with AI can be conceptualised from different perspectives and include a range of critical facets. Table 1 summarises our main insights.

Table 1
Summary of the responses to the polylogue's questions.

Author (s)	Q1: What kind of capabilities do people need in a world with AI?	Q2: How can we conceptualise these capabilities?	Q3: How can we help learners develop these capabilities?	Q4: How can we empirically study and assess the development of these capabilities?	Q5: What else should we consider?
DG	Self-regulated learning skills to adapt to changes and maintain agency while working with AI	A self-regulated learning perspective	Using AI to scaffold and provide personalised feedback	Developing unobtrusive AI-based techniques	We need to recognise hybrid human-AI regulation and develop a culture of using learning analytics for improvement
GS	Perform cognitive work where AI is less capable	A hybrid cognitive system perspective	Engaging with AI in daily knowledge work	Harnessing complexity science and modelling research methods	We may end up meeting AI halfway as more of our daily tasks will become structured and automated
RM	Be creative in uniquely human ways	A '4Cs' perspective	Using AI as a tool to encourage and support creativity	Developing tools that help assess creativity but keeping humans in the loop	We need to understand that both machines and humans contribute to creative outcomes
SP	Become deliberate about the use of AI	Sen's capability perspective	Developing self-awareness, understanding of AI and humanistic values	Studying learner change as a dynamic process across multiple dimensions and at different levels	Humanities are critical, including historical thinking, evolutionary thinking, philosophy, arts, literature, etc.
RMM	Create AI for human values	A human-centred AI perspective	Developing ethical and philosophical thinking for designing human-centred AI	Using authentic assessment practices in high-fidelity real life contexts	We need to adopt human-centred practices across many aspects of learning
SH/JT	Consider and use AI in relation to one's work and a larger system	A social realist perspective	Making AI visible and creating opportunities to gain experience	Using participatory and design-based approaches	The wider system is an important component when considering how capability will change
SK	Navigate one's own and others' views, mediated by AI	An AI-mediated discourse perspective	Engaging people in AI-mediated dialogue and groupwork	Using AI to identify a variety of classroom dialogues	It is fundamentally a question of values
SBS	Facilitate collective sensemaking using representational tools	A knowledge artistry perspective	Learning and practicing language, methodologies and artefacts of knowledge artistry	Using mixed methods to assess knowledge artistry process and outcomes	We need to empower citizens to engage critically with surveillance capitalism
MDL	Learn in the networks of humans and non-human intelligent systems	A networked learning perspective	Enabling communities to articulate alternative human-machine narratives	Using digital data to trace value creation in networked learning communities	We need to become conscious of how AI shapes our collective learning

These capabilities, as seen through our contributions, span from those primarily related to individual behaviour, cognition and dispositions to those that are related to the capabilities to engage in joint sensemaking and value creation. While some of us see those capabilities as fundamentally human, others acknowledge that these capabilities are hybrid and inseparable from AI tools that we use. Fig. 1 represents the distribution of our perspectives in this space. It uses the distribution of agency among individuals and collectives and between humans and AI as two primary axes. The X-axis shows whether the *capabilities are primarily seen as fundamentally human or hybrid* (i.e., distributed between and attuned to the capabilities of AI); the Y-axis shows whether these *capabilities are seen as primarily individual or collective* (i.e., distributed among multiple human agents).

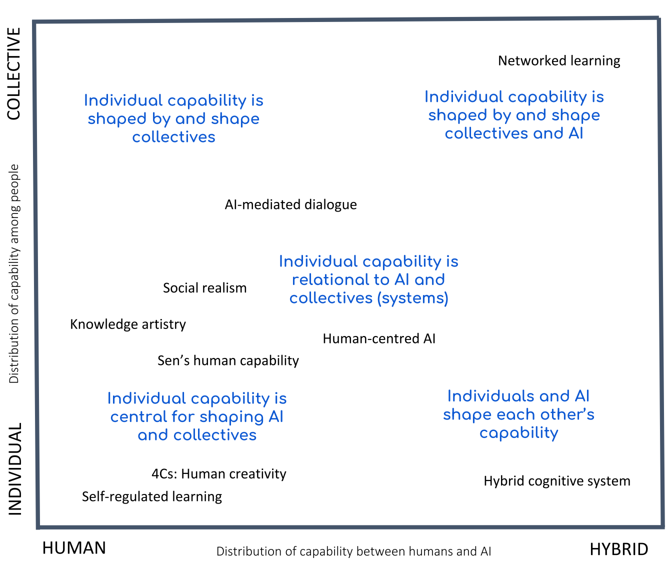

Fig. 1. Conceptual perspectives towards the capabilities for a world with AI represented in the polylogue from the distributed agency perspective.

Broadly, the perspectives in this space constitute five clusters, shown in blue colour in Fig. 1. In the bottom left corner are primarily those perspectives that view individual human capabilities as central for shaping AI and how it is used by people within groups, organisations and other collectives. This view is most richly represented in our polylogue, with self-regulated learning (DG) and 4Cs (RM) exemplifying it the best. In the bottom right corner of the figure are perspectives that see the individual capabilities for a world with AI as dependent not solely on humans but on the hybrids of humans and AI that mutually shape each other's capabilities. In our polylogue, this view is exemplified by the hybrid cognitive system (GS) perspective.

In the top part of the figure are perspectives that see individual capabilities as shaped by and shaping collectives of humans (top left) and hybrids of human collectives and AI (top right). In our polylogue, the former view is only partly represented by the AI-mediated dialogue (SK) perspective; but the latter is well exemplified by the networked learning (MDL) perspective.

In the middle of the figure are the perspectives that emphasise the relational nature of individual human capabilities for a world with AI. These perspectives emphasise that individual capabilities are inseparable from social, political, technical and other systems in which humans operate and simultaneously which they create. This view is well exemplified by the social realist (SH/JT), human-centred AI (RMM) and knowledge artistry (SBS) perspectives.

None of the perspectives are idealised theoretical models, and some firmly occupy a midway between several clusters. For example, Sen's human capability (SP) perspective focuses on individual capabilities and human agency, but it acknowledges that individual freedoms are inseparable from larger systems. This invites us to look further into what kinds of human capacities are actually needed for a world with AI.

Looking deeper, these capabilities broadly include two aspects. First, some of us (GS, SK, SH/JT) are explicit that these capabilities intertwine with a set of competencies directly related to AI, such as designing, interpreting, understanding, evaluating, and assessing algorithms and AI outputs. Others are less explicit that these capabilities need direct attention; nevertheless, most of us acknowledge that learners need to understand how AI functions and how it can be used. However, the focus is not on learning about AI but how AI shapes human thinking, interactions, and values—learning to live and learn with AI. From this perspective, our ideas move beyond *AI-centred* views of the capabilities for a world with AI (i.e., 'AI literacy' introduced earlier), and present three interrelated orientations: cognitive, humanistic and social. They are summarised in Fig. 2.

Cognitively oriented perspectives (represented by DG, GS and RM) emphasise human cognition, metacognition, and behaviour with AI. In this view, AI is a teammate or scaffold in a human-artificial cognitive system. Many of the underpinning capabilities, such as self-regulation and creativity, have been researched for decades, but they are complex and remain neither well understood nor well taught. Furthermore, AI changes how humans engage in cognitive tasks; therefore, people should learn to use AI tools in ways that augment their learning, behaviour and intelligence. For example, despite the well-documented benefits of SRL skills, and the numerous opportunities students have in schools and higher education institutions to explore, practice and hone them, SRL skills remain underdeveloped (Bjork, Dunlosky, & Kornell, 2013). Part of this problem is resources to address individual needs, such as providing necessary learning data and personalised feedback to learners so that they can effectively support the development of SRL skills. According to this perspective, AI-empowered systems could help address this issue. Such systems not only can support the development of SRL skills but also increase learners' skills to interact and work with AI.

Humanistically oriented perspectives (represented by SP and RMM) acknowledge the centrality of human values. It has been argued that we should promote capabilities that differentiate humans from machines, such as creativity, complex problem-solving and critical analysis and decision making, to keep people's relevance safe (Othman, 2019). However, advances in AI are already breaking new ground in the automation of these areas as well. AI algorithms are creating pieces of art that humans believe were created by classic artists (Iansiti & Lakhani, 2020), and are already solving problems considering huge amounts of evidence in ways that humans cannot easily perform by collaborating among themselves (Raisch & Krakowski, 2021). Once the human is not needed in the 'automation loop', what capabilities will remain important to make humans relevant? Therefore, these perspectives put at the centre humanistic ideals and capabilities of individuals to use and shape AI in ways that contribute to personal and collective wellbeing. While this orientation acknowledges that AI shapes human practices, it asserts that human agency to shape AI for human values is central. In practice, the implications fall both on equipping individuals with tools to question individual values when using technologies as well as choices made by those who design technologies. Questioning what values are embedded within the design (e.g., Friedman, 1996), and whether these values align with collective aspirations (Wenger et al., 2011) are just two potential directions towards developing a critical stance towards human-AI practices. Turning to humanities in education and adopting human-centred design practices are suggested as effective ways to imbue key human values into the AI algorithms and develop human agency to make free choices in regard to AI. Maintaining a broader outlook on mandatory curriculum that supports transferrable capabilities can be another way to support learners in navigating human-AI practices.

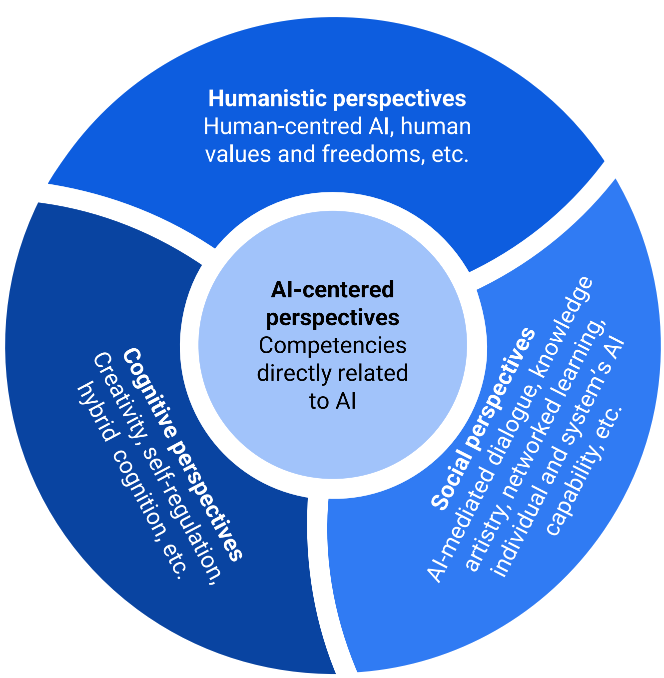

Fig. 2. Synthesis of different perspectives towards the capabilities for a world with AI.

Socially oriented perspectives (represented by SH/JT, SBS, SK and MDL) are less concerned with how AI affects individual cognition and behaviour; instead, they present a sociocultural focus on how AI mediates shared meaning-making and collective practices. Two kinds of capabilities tend to be central. Firstly, students and teachers' ways of using AI are shaped by social and cultural expectations of larger systems (e.g., schools). Therefore, the system's capabilities for using AI are as important as the capabilities of individuals. The development of these capabilities cannot be left unattended. Secondly, AI mediates and shapes joint meaning-making in collectives. Human capabilities to harness AI in ways that enhance these collaborative knowledge-making practices are central. As some of us point out, the networked learning communities are more than networks of humans; and the way human-machine relationships are formed in these networks impacts their capability to learn, solve problems and create value.

Our perspectives towards the capabilities for a world with AI also vary in terms of the *focus* (what these capabilities are for) and *locus* (where these capabilities are realised). Table 2 maps our perspectives in this space. None of the perspectives sits neatly within one category, but our mapping helps depict each perspective's dominant features and tendencies. While this was not known when we embarked on this

Table 2
Focus and locus of the capabilities for AI represented in the polylogue.

Focus of capability (what it is for)	Locus of capability (where it is realised/displayed)		
	Individual resourcefulness	Individuals in collectives	Collective practices
Person-focussed	*Self-regulated learning* Individual capability to self-regulate own learning	*Sen's capability* Capability to make free choices regarding AI	*Dialogic learning* Capability to understand multiple, mediated by AI, perspectives
Artefact-focussed	*'4C': Human creativity* Individual capability to produce novel solutions beyond AI	*Human-centred AI* Capability to design human-centred AI	*Knowledge artistry* Capability to facilitate collective sensemaking using visual representations
System-focussed	*Hybrid cognition* Individual capability to work with knowledge at the intersection of artificial and human knowledge systems	*Social realism* Individual capability supported by institutional capability to embrace AI	*Networked learning* Capability to learn in the networks of humans and non-human intelligent systems

exercise, Table 2 shows that our perspectives represent a whole spectrum of views along these two dimensions.

In terms of the focus, *person-focussed* perspectives emphasise the capabilities that agentic learners and citizens need to participate in a world with AI, such as regulating one's own learning, making free choices regarding AI, and understanding how AI mediates diverse perspectives. *Artefact-focussed* perspectives concentrate on the capabilities that enable people to engage in various knowledge practices and produce knowledge products that have value in a world with AI. These products involve diverse material, digital, symbolic and immaterial objects, such as creative solutions of problems, AI tools, and visual knowledge representations. *System-focussed* perspectives centre on the capabilities that are needed to create and participate in the distributed systems of humans and AI, such as to use outcomes produced by AI systems in human decision-making, to embrace AI as a part of institutional practices, and to participate in value creation in the networks of humans and AI systems.

In terms of the locus, some of our perspectives conceptualise the capabilities for a world with AI as primarily a matter of *individual resourcefulness*. Such capabilities are primarily realised when people engage in highly agentic and uniquely human forms of knowledge work, such as self-regulated learning, creative problem-solving and making sense of AI outputs. Other perspectives also see these capabilities as primarily *individual but related to the collective* capabilities, expectations and purposes. Therefore, individual AI-related capabilities are realised in relation to the shared goals, values, needs, institutional infrastructures, and support systems. Some other perspectives see these capabilities as profoundly intertwined with *collective practices*. Such capabilities are realised through joint dialogues, facilitation of collective sensemaking and participation in learning networks. This shows the need to move beyond an AI-centred view of capabilities and consider the capabilities that underpin the relationships between individuals, collectives and machines.

How to help learners develop these capabilities is a thorny question. There is not much to build upon. Long and Magerko (2020) propose 15 design considerations to help learners develop AI literacy, such as deliberately designing for explainability and transparency of AI decisions for learners, and enhancing opportunities to program for learners. However, how to design for capabilities that are not specific to AI yet firmly intertwined with it—such as to cooperate and share cognitive labour with the networks of humans and machines—is far less clear. Our ideas shared here suggest five broad approaches:

- *Explicit teaching*, which includes the development of students and teachers' AI literacy (SK, SH/JT) and humanistic thinking, such as ethics, philosophy, and historical ways of thinking (SP, RMM).
- *Authentic learning* that involves active engagement with AI in workplaces or other contexts (GS, SH/JT).
- *Critical thinking and reflective practices* that deepen understanding of how AI shapes and is shaped by human practices and cultures (SP, SH/JT).
- *Discourse and epistemic practices* that engage people in the shared creation of meanings through mastery of language, methodologies, artefacts, and other tools, including AI (MDL, SBS, SK).
- *AI-mediated learning,* where AI is a scaffold for mastering the most complex human capabilities, such as creativity and self-regulation (DG, RM).

This list is only indicative and inevitably incomplete. Nevertheless, it suggests that educators will likely need to master a rather broad pedagogical toolkit and combine it with AI in a range of different ways.

AI has already made inroads into the formative and summative assessment. Such practices as automatic essay scoring and personalised feedback are increasingly becoming widespread in school examination practices and universities (Dixon-Román, Nichols, & Nyame-Mensah, 2020). However, how to assess human capabilities to function productively in a world with AI has been barely touched (Bearman & Luckin, 2020). Our suggested ideas about how we could study and assess these capabilities broadly point to three critical directions.

First, such capabilities likely will need to be empirically studied and assessed in *authentic contexts* (RMM, SH/JT). Secondly, while complex human capabilities are unlikely to be assessed fully by machines alone (GS, RM), *AI-based approaches* could be helpful (MDL, SK), and their possibilities yet have not been fully explored (DG). Thirdly, while the combination of methods could offer some robust insights into learning processes and outcomes (SP, SBS), further assessment advancements will require embracing *new theoretical ideas*, such as complexity theories and modelling (GS).

5.2. What have we learnt from this?

Our conceptualisations vary across a range of dimensions, such as who benefits (individual vs. society) and what is the rationale (economic vs. social). Some of us point out the importance of some well-known, but hard to learn general human capabilities, such as self-regulation and creativity; others emphasise new kinds of capabilities that are firmly entwined with AI, such as participating in dialogues and creating knowledge in the networks of humans and AI.

Some conceptualisations place a strong emphasis on economic value, which in current policy debates is often expressed in terms of 'human capital'. This primarily concerns what OECD describes as "the knowledge, skills, competencies and other attributes embodied in individuals that are relevant to economic activity" (OECD, 2019, p. 104). In contrast, other notions emphasise the human agency in defining and pursuing valued—collectively or individually—choices. Moreover, some notions suggest that AI itself will play a major role in helping learners develop the capabilities they will need to confront the AI disruption. In contrast, other notions emphasise the role of design, humanities and philosophy to identify key human values that should shape the future interactions between humans and machines. In this way, we can consider the ways AI is both shaped by and can shape human capabilities. AI can support learning and allow people to extend their abilities into under-explored areas.

It also must be noted that there is a natural tendency to consider 'capabilities' with respect to individual learners, and in particular learners as school and university students. However, our dialogue suggests that the capabilities must be seen in the broader context of the systems in which we live, learn and work. Indeed, *capabilities* may be conceived at an individual level, and a systems or organisational level, recognizing their mutually constitutive nature and the importance of systems of learning.

Further, the development of these capabilities is not individual, but rather a social consideration. To develop these capabilities in students, teachers must also possess those capabilities. Yet, these capabilities, as we have expressed, extend well beyond digital AI-enabled tools to include shared practices. Therefore, the question is how AI changes the world around us and how we choose to engage with AI as part of that world.

Post-Snowden, Cambridge Analytica, Brexit and US Elections, we understand much more clearly how society's perception of reality is increasingly mediated via commercially owned platforms, refracted through algorithmically warped lenses. Awareness is growing of the need for citizens to stay in control of their attention, as trillions of dollars of investment by companies seeks to distract it. However, it is evident, and unsurprising, that many citizens remain unable to combat this attentional warfare. In this asymmetric context, citizens are no longer making a 'free choice', as is typically pleaded by social media platform owners. The emancipatory potential of education, which seeks to liberate learners by giving them ethical agency, now requires that we cultivate citizens' capacity for sensemaking in the context of 'surveillance capitalism' (Zuboff, 2019). This equips citizens to understand the vital importance of sensemaking in maintaining a functioning democracy, and one hopes, the confidence to engage in civic life more effectively. Thus, we see how personal learning capabilities, if amplified by millions, should have network effects that unavoidably assume social, humanistic and political dimensions.

6. Concluding remarks

Our polylogue productively extends current discussions about AI-related capabilities. It convincingly reveals that the answer to the question "What capabilities do learners need for a world with AI?" should not be limited to an AI-centric focus on how to teach basic or even advanced AI literacies, but rather, requires broader, richer ways of thinking about what these capabilities may entail. Our contributions, jointly taken, revisit the capabilities needed for a world with AI from the three, partly overlapping, perspectives: cognitive, humanistic and social. These perspectives shift the focus from what we need to learn about AI to human cognitive capacities, values and joint knowledge practices needed for success in a world with AI. *Cognitive/Humanistic/Social*—or any other classification scheme—are of course labels of convenience to help cluster perspectives in helpful ways, but these angles of analysis are without doubt intersecting and mutually shaping.

It is evident that our different worldviews strongly influence our perspectives about and expectations of AI. For example, we come from varied disciplinary backgrounds, so our knowledge about AI is different. Some of us have used or coded AI algorithms and know, for example, that many important decisions are ultimately made by the programmer. At a larger scale, people in some geographical areas may have completely different perspectives about the effects of AI because the development and use of AI are not uniform across countries and sectors within each. This makes AI a very powerful and potentially disruptive phenomenon. It is not easy to pin down a definite set of the capabilities that learners will need to survive the disruptions that will impact the various sectors of our global society in widely different forms, to different extents, and in unpredictable ways. It is even harder to say what kinds of capabilities will enable people to thrive in a world with AI. Nevertheless, it is clear that we need to move beyond AI-centred views of capabilities and consider the ecology of technology, cognition, social interaction, and values. We need to be more fluent at understanding different disciplinary perspectives and participate in such polylogic discussions more often (Markauskaite & Goodyear, 2017; Matusov et al., 2019). These capabilities are so important because they underpin our democratic society, human wellbeing, and sustainable planet.

In conclusion, humanity is the only species that invents and continually evolves tools. Just as physical tools gave us unprecedented ability to shape our material environment, the symbol systems we have evolved as tools for thought have utterly transformed *how* we think, and *what* we can think. With the invention of writing, we moved from oral cultures to literate cultures, and humanity could question established ideas in new ways, and imagine possible futures that were too complex to explore without writing (Ong, 1982). The printing press was another transformative agent of change (Eisenstein, 1979), and digital infrastructures changed the global conversation again. Crossing each of these thresholds had cognitive, social, political and cultural ramifications. We stand now on the edge of a future in which our tools have a degree of agency, and already possess specialised cognitive and coordination capabilities that eclipse our own. Reimagining what it means to live, learn and work in partnership with AI is awe-inspiring, and brings profound responsibilities. It is hoped that the perspectives explored in this paper inject urgency into the need to accelerate and deepen this conversation.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Each invited co-author made a substantive contribution to the argument. The order of the names does not reflect the extent or value of their intellectual contribution. In the spirit of equity, we first listed early career researchers and then senior academics.

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