Reconceptualizing AI Literacy: The Importance of Metacognitive Thinking in an Artificial Intelligence (AI)-Enabled Workforce

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***Abstract*—We propose that metacognitive skills and metacognitive thinking will become increasingly important for effective use of AI (Artificial Intelligence) systems. As the collaborative capability of AI systems improves, humans will spend more of their time working with AI. This is expected to uniquely influence the human decision-making process. We identify four characteristics that differentiate human-AI interactions from human-human interaction, each of which is likely to affect our thinking and decisions. These are (1) the accuracy of our cognitive heuristics for predicting the behaviour of AI systems, (2) AI's limited capability when dealing with novel and ill-defined problems, (3) the lack of a natural, reciprocal feedback mechanism in AI systems and (4) the inability of AI systems to engage in metacognition. Drawing upon the dual-process theory of human thought process, we argue that these characteristics will diminish the efficacy of the system one mode of human thinking, making metacognitive thinking skills important to ensure effective use of AI systems. We conclude by describing how this need can be addressed through training and AI design.**

***Index Terms*—Artificial Intelligence, metacognition, cognitive heuristics, cognitive bias, society, skills, decision-making**

I. Introduction

Artificial Intelligence (AI) technologies have been advancing rapidly, particularly with the development of Large Language Model (LLM) powered systems. Studies exploring the performance benefits associated with the use of large language models (LLM) suggest that these tools improve both productivity and quality in a wide range of domains [1]–[4]. Importantly, improvements in fields such as computer vision and natural language are making AI systems more collaborative. Consequently, we are likely to see workers interacting with AI systems to perform a complex task or series of tasks rather than simply using an AI system to automate a specific function [5]. The range of tasks that AI can support is also expanding. It is therefore critical to understand what skills workers need to use AI systems effectively.

We contend that when humans work with collaborative forms of AI (such as Large Language Models), the human and the AI mutually influence one another. The human directs the AI and determines how to use the output of the AI but the AI's responses, the dynamics of interaction, and the frequency of these interactions will also affect human decision-making processes. However, human decision-making often relies on cognitive heuristics that were primarily designed for interactions with other humans. It is therefore important to consider how interactions between human workers and AI systems are likely to differ from interactions between two or more human workers. Below, we identify four characteristics that differentiate the experience of working with AI from working with a human worker. We also show that metacognitive skills and metacognitive thinking will mitigate the impact of these characteristics.

II. What is Metacognition?

Metacognition, in simple terms, is defined as "thinking about thinking" [6]. Metacognitive skills involve the ability to monitor, regulate, and control one's own cognitive processes [7]. Before embarking upon a task, metacognitive thinking allows an individual to plan what course of action to take, while also accounting for possible outcomes of these procedures. When actually performing the task, an individual engages in metacognition by monitoring their thinking processes, evaluating the quality of the information they are using, checking if the strategies they have chosen are effective and revisiting the task objectives to check that their solution matches the task's needs. At the completion of the task, metacognitive thinking involves reflecting on what worked or did not work and, if necessary, determining how to approach the task more effectively in the future [8]. While solving a problem, metacognitive processes help individuals change their mental representations as they continuously engage in thinking about what they know, what needs to be achieved and what limitations they would face [9].

These cognitive processes are likely to play an increasingly important role for workers who use collaborative AI systems, for the reasons we outline below.

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III. Differentiating the Experience of Working with AI and Working with Other Human Interactions

A. Cognitive heuristics become more dysfunctional

One of the factors that has the potential to hinder humans in working with artificial intelligence is the cognitive heuristics that humans have developed based on their experiences interacting and working with humans. Cognitive heuristics (also known as cognitive biases) are mental shortcuts that we have developed to help us make decisions with limited information and time [10], [11]. Cognitive heuristics are a feature of system one thinking, which means that they tend to be initiated automatically rather than consciously [12].

Traditionally, these heuristics represent an important part of an expert's proficiency, as they have formed because of extensive involvement in a field of knowledge [13]. However, when applied inappropriately, these heuristics turn into biases because they oversimplify complex situations, leading to errors in decision-making [12].

The introduction of Artificial Intelligence (AI) as a collaborative partner initiates novel heuristics and exacerbates pre-existing cognitive biases, as the near-human resemblance but distinct technical capabilities of AI systems alter their utility. In addition, humans commonly anthropomorphize AI systems, attributing human-like characteristics to the AI [14]. This tendency is likely to result in humans applying the above cognitive heuristics (originally designed to predict human behaviour) to AI systems.

Cognitive heuristics that were developed to predict human behaviour are likely to be dysfunctional when they are applied to AI because the behaviour and performance of AI systems differ systematically from that of humans. For example, humans have general intelligence, which means that their performance on one task is likely to predict how well they perform on another type of task. Hence, we rely on a cognitive heuristic known as the halo effect, using a person's performance on one task to determine whether they will perform well on another task. However, AI does not (yet) have general intelligence [15], which means that it can perform extremely well on the tasks that it has been trained to perform and very poorly on tasks that it has not been trained to perform. Tools such as ChatGPT present well-written solutions or answers. However, as some have unfortunately discovered to their cost, the quality of its writing is not a reliable indicator of the accuracy of its output [16].

In Table I, we list other well-known cognitive heuristics and explain why they are likely to be more dysfunctional in the context of working with AI. Metacognition will play an important role in promoting awareness of one's own thinking and diminishing reliance on cognitive heuristics when working with AI.

B. Spending more time on novel and unstructured tasks

AI outperforms humans in its computational power, making it far better at processing large amounts of data, recognizing patterns and predicting outcomes [20]. However, AI systems are inferior to humans when it comes to dealing with tasks requiring physical and psychomotor abilities, working in an unstructured and unpredictable environment, social interaction and intuitive decision-making [21]–[24]. Consequently, in the division of labour between human worker and AI system, the human worker will be responsible for non-routine, unstructured or novel aspects of the work [25], [26].

Novel and unstructured work usually requires more deliberate, conscious mental effort [27]. This is due to the absence of readily available, learned strategies. Using their metacognitive skills, human workers can draw upon their broader experience to identify ways in which this task is familiar or similar to others that they have encountered. This awareness allows the human to suggest ways of defining or approaching the task that make it amenable to being performed by the AI [28].

The role of the human extends beyond providing structure or context for the AI system. It includes recognizing non-routine or novel elements within the context or situation that may render the AI's response suboptimal. Humans will also be responsible for ongoing monitoring and evaluation of AI output to identify instances where it proves inappropriate, typically due to unexpected circumstances or misinterpretations by the AI. This is because AI systems lack the contextual information and general knowledge that humans possess [15], which means that it is ultimately up to the human to interpret the broader environment and the task objectives to ensure that the output being generated is appropriate and optimal. This requires the human's metacognitive ability to evaluate the quality of information and monitor the output being produced in relation to the task objectives. Therefore, the human worker not only handles novel tasks but also remains alert (using metacognition) in recognizing situations that would necessitate their intervention.

C. Collaborating without interaction cues

AI systems also lack the rich interaction cues that humans use to communicate with one another. When working with humans, norms such as cooperation, shared understanding, and mutual responsibility govern the interaction [29]. Human interactions are rooted in the concept of 'grounding', which is the "continuous seeking and providing of evidence about what has been said and understood..." [30]. Grounding takes various forms and includes the use of gestures, voice intonation, facial expressions, non-verbal body cues. When human interlocutors are not able to see one another, emojis and emoticons are used in their place [31]. These non-verbal communication cues convey much of the meaning in human-to-human interaction [32], since they are commonly used to communicate agreement, understanding, emphasis or conversely, uncertainty, humour, dissatisfaction and disagreement [33], [34]. They signal when a recipient seeks further clarification, has additional information or disagrees with what is being said.

These non-verbal communication cues, which are so important for effective communication and collaboration, are not available to humans when working with an AI system. The

TABLE I
COGNITIVE HEURISTICS

Cognitive Heuristic	Effect when applied to AI systems
Anchoring Bias: Giving more weight to the first piece of information we receive [17].	When AI systems provide the initial response to a problem, the anchoring bias limits the range of potential solutions considered by the human worker. The anchoring bias is likely to be more detrimental in the context of working with AI than it is when working with humans. This is because natural conversations between humans and AI lack the back-and-forth exchange of ideas that occurs in human-human interactions. In the latter case, the anchoring effect has a higher likelihood of being mitigated due to the more dynamic flow of conversation. Additionally, when working with humans, individuals can subconsciously gauge the confidence level in the information provided by their human counterparts. However, this capability is not present in AI. Given the objective and authoritative manner in which many AI systems respond, it becomes easier to succumb to the anchoring heuristic in human-AI collaboration compared to human-human collaboration.
Confirmation Bias: Seeking information that confirms our beliefs without looking for alternative information [18].	AI systems have much greater information processing capability so they can draw upon a much larger pool of data to inform their responses than a human worker. Therefore, when a human user seeks information that confirms their exists beliefs from the AI, the AI is more likely to be able to provide information that substantiates these beliefs (even if there is far more information to support an alternative belief. Furthermore, unlike a human worker, the AI system will not volunteer this disconfirming evidence unless specifically asked (or designed) to provide both confirming and disconfirming evidence.
Overconfidence Bias: The tendency of individuals to have more confidence in their in their own skills and moral judgments than is justified by their performance [19].	In the context of collaborating with AI, the tendency to overestimate one's abilities may discourage humans from seeking input from the AI. Whereas human workers offer unsolicited advice or recommendations when they perceive a need, AI systems lack the nuanced situational awareness to inject unsolicited feedback, exacerbating the effects of the overconfidence bias and limiting the potential benefits of AI collaboration.

AI's feedback is limited by its design which means that it may not communicate or even recognize when it lacks all the information it needs to perform a specific task. It has fewer channels and opportunities to signal when it seeks further clarification or can offer additional or conflicting information. In the absence of the rich, multichannel and continuous communication system used between humans, humans working with AI systems need to serve as their own 'critical friend'.

Our metacognitive thinking involves the use of questioning, perspective-taking, monitoring and evaluation, and therefore provides an internal source for the some of the ongoing and nuanced communication that a human would provide. . Metacognitive skills allow individuals to make more accurate judgments about their own knowledge and performance [35]. Metacognitive skills also help us to identify and evaluate alternative information and strategies, and adjust our approaches and decisions based on metacognitive feedback [36]. Although our metacognition will often lack the diversity of perspectives and information that another human would provide, it can lessen the effect of AI's limited communication and feedback.

D. AI lacks metacognitive capability

Finally, most AI experts agree that AI will not achieve self-awareness in the short-term [37]. Consequently, AI cannot think about its own thinking and is not capable of engaging in metacognition. However, metacognition is a core capability using which humans judge their decisions. They often know when they have made a mistake, even without direct feedback, and they can tell how confident they are in a decision, which usually aligns with actual performance [38]. These metacognitive skills help individuals to avoid repeating errors and prevents them from spending too much time or effort on choices that are not based on evidence. Another human with metacognitive skills can help us assess the assumptions behind our decisions in a shared task. AI systems cannot self-monitor or evaluate their own decisions. Therefore, the task of evaluating both our own and the AI's 'thinking' becomes a key skill humans contribute to ensure the shared goal is being met. In collaborations with AI systems, the human is likely to be ultimately responsible for metacognitive functions such as planning, monitoring and evaluation. When performing a task, cognitive skills are essential for executing the typical actions associated with that task. Such typical actions can often be performed by AI but metacognition adds value through using awareness and oversight to not only ensure that the correct steps are being followed but also to assess if the task is progressing as expected and make any necessary adjustments along the way. As a uniquely human capability, metacognition is likely to become an increasingly valuable, AI-complementary skill.

IV. Using metacognitive skills to work effectively with AI

Above, we attempted to draw out some of the ways in which metacognitive thinking can address the differences involved in working with AI systems rather than human collaborators. In this section, we draw upon research into metacognition to justify these propositions.

First, metacognition has been found to reduce our reliance on cognitive heuristics [39]–[41] as it encourages individuals to assess the broader context, effectively monitor their performance, and recognize when they might be making errors [10], [42], [43]. With AI introducing a new way of making decisions [44], this capability to train our minds to use these metacognitive processes to identify and counter these biases will become critical .

Second, whereas our cognitive heuristics can be functional when dealing with well-known situations or tasks, the slower system two thinking and benefits of metacognition are most beneficial when dealing with novel tasks or ill-defined contexts. This is because they facilitate creation of mental representations of the essential structural characteristics of a problem, which can be easily generalized to newer problems that have different surface features [45], [46]. Metacognitive skills improve our ability to transfer our knowledge and skills to new and unfamiliar contexts [47]–[49]. In a novel situation, we need to take the time to think what we know and how we have approached similar tasks before and what worked and didn't work – all forms of metacognition.

Finally, metacognition has been found to serve as a replacement for external feedback. Researchers have found that students' performance improves when they use self-questioning when they are learning in the absence of external feedback [50]. This self-questioning helps their understanding of a topic to change and evolve, thereby improving their learning.

V. Strengthening metacognition for humans working with AI

If metacognitive skills are increasingly important in an era of AI-enabled work, how do we ensure that workers are engaging in metacognition? Metacognitive skills are not well represented in skills taxonomies [51], [52], but they are commonly used in educational environments [53]. In the context of humans collaborating with AI, they are likely to have much broader application.

Training in metacognitive skills involves promoting awareness and reflection about one's thinking, strategies and decisions. Researchers recommend a number of specific instructional strategies to promote metacognition in students, addressing both cognitive knowledge and cognitive regulation. Such training instills a thorough understanding of when, how, and why to use strategies, as well as provides meta-level instructions focusing on the awareness and management of metacognitive processes [54]. Prompts and checklists with clear sub-questions that guide planning, monitoring, and evaluation are effective and commonly adopted metacognition training tools in the field of education [55]. Reflective journaling, wherein participants write about their learning experience and develop strategies for improving their approach in the future has also been found to improve performance in students. Furthermore, metacognitive feedback reminds individuals to review and improve how they are using thinking strategies while performing a task [36]. This kind of feedback is usually in the form of communication that explicitly brings the individual's attention to the cognitive strategies in use and their efficacy in the context.

There is also potential to design AI tools so that they prompt their human users to engage in metacognition. However, this alone may not suffice to comprehensively address the need for metacognitive thinking. This is because AI design can only address that which we anticipate. For everything else we will still depend on our human intelligence and in particular, metacognitive thinking.

VI. Future research

In this paper we have presented a rationale for focusing on metacognition as an enabler of effective use of collaborative AI tools. Further research is needed to test our theory and progress this line of research. Key questions that need to be answered include:

1) Do people who engage in more metacognitive thinking also experience more benefits from using collaborative AI tools?
2) Are metacognitive interventions effective in increasing performance when working with collaborative AI tools
3) Does the type of work being carried out affect the importance of metacognition for effective use of AI tools? For example, is metacognitive thinking more important when using AI for knowledge work compared with creative work?
4) Can AI systems be designed to promote metacognitive thinking and thereby improve performance for humans working with collaborative AI tools?

At an advanced stage, further questions arise, such as how to tailor metacognitive processes for experts versus novices in a given task, when to incorporate metacognitive prompts into the human-AI collaboration workflow, and how to enhance metacognitive accuracy through AI design.

VII. Implications of the discussion

The above discussion of our reliance on the use of mental shortcuts for decision-making processes underscores the need for metacognitive thinking where workers need to understand their own thought process when working with the AI. This will enable them to identify when to use an AI, anticipate potential failures and adjust their collaboration strategies with the AI accordingly.

Engaging in metacognitive thinking requires practice. However, at a basic level, it is about understanding the inner workings of our brain. This understanding can empower us to take control of our thoughts. Research suggests that our brain operates in two distinct modes [56]: one where we function on autopilot, and another where we are more focused and aware. When collaborating with AI, it is easy to rely heavily on the technology and remain in autopilot. However, effective collaboration relies on our ability to recognize and leverage each other's strengths and weaknesses.

One effective technique for training the brain to transition from autopilot to a state of heightened awareness is mindfulness [57]. Mindfulness helps us shift from merely reacting to being consciously aware of our thoughts, thereby promoting metacognition [58]. At its core, mindfulness involves concentrating on a single thought or object and gently guiding the mind back when it wanders [59].

VIII. Future directions for the research

Our first step towards testing the proposition that metacognitive skills would facilitate performance when working with AI is to develop and validate a measure of metacognition when working with AI. With such a measure it would then be possible to test whether people who engage in more metacognition whilst collaborating with the AI also experience more productivity or greater accuracy from using the tool. We would also want to test whether the measure of metacognition explains variance in performance above and beyond that explained by AI literacy. We plan to adapt an existing measure of metacognition from [60] by re-wording items to focus on planning, monitoring and evaluation when working with AI on a task. We also plan to adapt a measure of AI literacy from [61] so that it is possible to also test whether the effect of metacognition on performance can be differentiated from the effect of AI literacy.

IX. Conclusion

By analysing features of human-AI collaboration that differentiate it from human-human collaboration, we illustrate the need for metacognitive thinking to support effective use of collaborative AI tools. Research into this topic can address the questions that are being raised regarding what skills and knowledge will be important for workers who collaborate with AI systems. This work also can support education and training initiatives and the design of AI systems that complement human cognition.

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