The Cognitive Cost of Generative AI
Mapping long-term risks and moderating factors

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Abstract

Generative AI (GenAI) technology has rapidly become an omnipresent technological aid in knowledge work. GenAI has the potential to support and automate some of the cognitive skills considered essentially human, such as analytic problem solving, planning, and creativity. While the promise of increased productivity, efficiency, and accuracy is appealing, such extensive adoption begs the question: What is the cost of outsourcing cognitive tasks to GenAI? When does aid become substitution, and what is the long-term impact of doing this continuously? Like muscles atrophy without stimulus, research has indicated that cognitive skills deteriorate if not regularly exercised. Researchers globally are still discovering the task-specific benefits and adverse consequences of deploying GenAI in various knowledge work processes, but no one yet knows the long-term impact of using GenAI to support cognitive processes, and we have limited technological antecedents to rely on. This position paper provides a mapping of existing research and synthesizes it into an outline of potential long-term risk areas for cognition of using GenAI in knowledge work.

CCS Concepts

• **Human-centered computing → HCI theory, concepts and models**.

Keywords

Generative AI, cognitive cost, critical thinking, long-term impact

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1 Introduction

Generative AI technology (GenAI[1]) has become pervasive in knowledge work processes in a comparatively short amount of time. ChatGPT became the fastest growing software in the history of web applications within two months of its launch [27], and AI is being deployed into platforms we use daily to communicate, work, and create. The novelty of GenAI models lies especially in their capacity to *infer* from natural language input and mimic processes associated with knowledge work – from analysis of complex texts to creative writing. According to the Microsoft 2024 Work Trend Index Annual Report, 75% of global knowledge workers already use AI [50]. In a knowledge economy, these technologies are disruptive. Goldman Sachs research has estimated that GenAI technologies could expose the equivalent of 300 million full-time knowledge-intensive jobs to automation [10].

But technology is not neutral [41]. One one hand, GenAI technologies promise increased productivity and creativity in a vast amount of knowledge-intensive industries (e.g., [11, 51, 72]). GenAI technology holds the promise of enabling knowledge workers to produce more work of higher quality than ever before. On the other hand, we know little about the consequences of outsourcing essential cognitive processes to GenAI (e.g., [6, 24, 46, 48, 59]) According to the "use it or lose it" hypothesis, cognitive capability and reserve declines when not regularly exercised [24, 46, 64]. Several empirical studies have begun to identify detrimental cognitive impact of using GenAI in short-term processes, e.g., less learning [17], worse knowledge retention [1], reduced brain-connectivity [40], over-reliance on algorithmic prediction [30], and reduced ability for critical thinking [26, 44, 62].

Why cost? This paper provides a critical perspective on the application of GenAI in knowledge work by focusing on cognitive *cost*, rather than *impact* more broadly (which could be both benefits and adverse effects). This is motivated by the ambition to understand the full impact of technology in application: "When you invent the ship, you also invent the shipwreck; when you invent the plane you also invent the plane crash; and when you invent electricity, you invent electrocution. Every technology carries its own negativity, which is invented at the same time as technical progress." [66]. The *benefits* of GenAI are amply promoted by large tech corporations who are eager to push the sales of their product, while it is less obvious who stands to gain from the critical study of the same technologies. Independent research is necessary to advance our understanding of the full implications of novel technologies so policies can be created

[1] I consider "generative AI" to encompass models which are are able to generate "new" data such as text, images, audio, and so on.

from an informed position, rather than according to the agenda of tech firms [69]. Furthermore, the mapping of *moderating factors* to potential long-term cost may provide avenues for the design of mitigation strategies within the design of GenAI interfaces and applications.

2 Generative AI in knowledge work

All research suggests that GenAI is being used heavily in processes which require essential "21st century skills", such as critical thinking, creativity, metacognition, and problem solving [8, 22, 70]. One survey showed that 42% of ChatGPT users use it for researching a topic or generating ideas, and 26% use it for drafting longer documents [14]. More recent research shows that use cases have shifted towards therapeutic, organizational, and learning purposes [70], suggesting significant cognitive impact beyond professional skills and abilities.

Most research shows that knowledge workers are largely positive about the use of GenAI use in their professional work, e.g., [14, 29, 32]. Users especially highlight that GenAI helps them be more productive and satisfied by increasing both their quantity and quality of output [11, 19]. Some studies indicate that benefits apply asymmetrically. The use of GenAI technology primarily benefits workers below the average performance threshold [19, 73], which implies that it is likely that AI usage will affect different workers with different skillsets disproportionately.

A recent meta-study showed a positive association between mental effort and negative affect of tasks, suggesting that mental effort is inherently aversive [18]. It makes sense, then, that offloading mentally challenging tasks to GenAI leads to positive feelings of cognitive relief and enhanced creativity. However, substantial empirical research has shown that more cognitively complex work is related to better cognitive functioning later in life, and vice versa [2, 9, 23, 25, 45, 52, 58]. A subset of these studies even identified cognitively complex work as being associated with a lower prevalence of cognitive impairment and dementia [2, 52]. **GenAI potentially introduces a discrepancy between the desire to avoid cognitively challenging tasks, versus improved cognitive outcomes in later life for individuals who routinely engage in cognitively challenging work**.

It is clear that GenAI introduces fundamental changes to how knowledge work is carried out and the tasks knowledge workers engage in (even the metacognition involved in evaluating which type of tasks are suitable or not suitable for supplementation by GenAI functionality is likely to impose new tasks [44]). In the below sections, I outline three *identified risk areas* based on existing research. These are areas where experiments have found some evidence of short-term adverse cognitive effect brought about by the introduction of GenAI, but where we do not know the long-term impact. They therefore provide empirically substantiated hypotheses worth creating long-term empirical measurements of.

3 Cognitive offloading → skill degradation

Cognitive offloading is the event of taking physical action to reduce the cognitive demands imposed by a task, such as setting a smartphone reminder of an event or writing an idea down on a napkin to avoid forgetting it [31, 33, 54]. Cognitive offloading is necessary to allow us to complete many tasks because it frees up cognitive resources to focus on other tasks. However, continued offloading or outsourcing of cognitive load can decrease our inherent ability to perform certain tasks. According to the "use-it or-lose-it" hypothesis, an individual's level of cognitive functioning is determined by two mechanisms: *differential preservation* (cognitively active individuals have higher initial levels of cognitive ability) and *preserved differentiation* (cognitively active individuals show less cognitive decline over time) [7, 24]. According to the cognitive reserve hypothesis, engagement in mentally stimulating activities and environments is linked to increased neuronal development, which leads to the development of more cognitive reserve (and therefore, resilience to cognitively adverse events) [24, 58, 64]. **A central hypothesis is that excessive cognitive offloading or even replacement of entire cognitive processes by GenAI may cause higher-order cognitive skills to decline over time, either via impoverished development of these skills, or the absence of exercising and maintaining them** [3, 6, 46, 59]. Findings by Loh and Kanai [47] indicated that *the internet* has led to shallower information processing and decreased information retention brought about by hypertext environments and constant access to information (reducing the necessity for deep processing to commit knowledge to long-term memory). The shallow-learning effect is likely to be even more pronounced in the case of Large Language Models (LLMs). A recent study found EEG-evidence that brain connectivity systematically scaled down with the amount of external support, so people who wrote essays with the aid of LLMs showed weaker brain connectivity than people who used a search engine, who again showed weaker brain connectivity than those who wrote without any external aid. Stadler et al. [62] confirmed that students using GenAI to research a subject *did* experience decreased cognitive load compared to students using a traditional search engine, however, the students using GenAI demonstrated lower-quality reasoning and argumentation in final assignments.

4 Over-reliance → Reduced critical thinking

A second risk area is the propensity to over-rely on the output of GenAI due to an inflated sense of trust in the performance of the technology. **A central hypothesis is that over-reliance or misplaced trust in GenAI output may lead to worsened decision-making and critical thinking skills over time.** There is a considerable empirical gap: studies of critical thinking with GenAI show mixed or inconclusive results, often due to small scales samples and/or inadequate methodological design [53]. While some empirical studies claim that GenAI raises students' critical thinking skill, e.g. [55, 60, 68], other recent studies find that use of AI tools correlated with *lower* critical thinking ability [26, 44]. All existing empirical studies are *short-term* studies, and many are based on self-report and surveys, meaning they study *self-perceptions* of critical thinking rather than actual effect, e.g., [44, 55].

A significant body of research suggests that AI-assisted teams systematically under-perform compared to AI alone in tasks where the accuracy of an AI is higher than humans working alone (e.g., [5, 28, 36, 43, 71]), however, the long-term effects are unknown. It is a possibility that increased sophistication and output quality of GenAI systems will lead knowledge workers to exert less critical evaluation of their performance: *"if you make hallucinations rare enough, people become unfamiliar with what they look like and they stop looking for them"* [34].

Possible cause	Possible moderating factors	Possible long-term effect (cost)
Identified risk areas:		
Cognitive offloading	Shallow inform. processing [47] Cognitive strain avoidance [37] Shortened problem-solving [57]	Skill degradation
Over-reliance	Reliance on general heuristics [12, 26, 44] Anthropomorphization, e.g. [15]	Reduced critical thinking ability
Reduced sense of agency Creative displacement anxiety [13]	Outperformance by AI [56] Placebo effect [39]	Reduced self-efficacy Overinflated self-efficacy Worsened self-regulated learning
Hypothesized risk areas: Social cognition? [14] Metacognitive ability? [54] Technostress? (e.g., [42])		

Table 1: Identified risk areas (based on state-of-the-art research) provide an initial point-of-departure for further investigation and have been shown to cause adverse short-term effects. Hypothesized risk areas provide directions for exploration, but have not yet been studied or evaluated.

5 Reduced sense of agency → Effects to self-efficacy and self-regulated learning

Perceived self-efficacy is a significant component in an individual's cognitive development and functioning. Self-efficacy shapes an individual's motivation, emotional states, and behaviors [4]. **A central hypothesis is that reduced agency and creative displacement [13] brought about by GenAI my lead to changes in self-efficacy and/or worsened self-regulated learning**. Workers with a strong belief in their own creative abilities, i.e., workers with a higher sense of creative self-efficacy, tend to have higher confidence in their job performance through their self-assessed personal accomplishment [63]. As personal accomplishment increases, so does an individual's motivation, productivity, creativity, and problem-solving abilities [49]. However, even seemingly insignificant skills being performed better by AI can negatively affect our self-worth and sense of agency [38, 56]. Schaap et al. [56] showed that when outperformed by AI, humans felt inferior, experienced less agency, and had a less positive attitude towards the AI system [56]. In a diary-study, Kobiella et al. [38] showed that workers' *sense of accomplishment* when working with ChatGPT was negatively impacted by a lack of challenge of the task, diminished sense of ownership, and inferiority: participants simply believed their ideas could not compete with the AI-generated content. Conversely, other studies have found users to *over-estimate* their own ability when and after they believe they are assisted by AI, even when they are not, a so-called *placebo effect* [39, 65]. Writers who create texts with the aid of ChatGPT report a reduced sense of ownership, although refrained from disclosing AI-assistance in public, dubbed the *AI ghostwriter effect* [21].

Whether people over- or under-estimate their own ability as a result of using GenAI, the impact on self-efficacy could be that these attribution tendencies interfere with self-regulated learning [61]. Learners could develop the impression that their abilities are much higher than they actually are, possibly leading them to the conclusion that they need less further practice. Conversely, feeling creatively displaced or outperformed by GenAI could stifle cognitive development by reducing motivation to practice or perform a task.

The hypotheses and their possible moderating factors identified by previous research is shown in Table 1. Importantly, these are not necessarily risks to the *products* of knowledge work, such as the quality or type of output produced by knowledge workers. Recent research has also pointed to numerous examples of adverse impacts on the *output* of knowledge processes, e.g., the risk of loss of collective novelty in creative problem solution [20, 35], "mechanized convergence", the tendency of individuals who use GenAI to produce less diverse output, e.g., [44, 67], or reduced quality solutions when the task is outside the frontier of AI functionality [19]. Exploring the cognitive cost of GenAI use to *processes* implies thoroughly investigating the causal structure of each risk area. Additionally, research in this area is likely to discover many new facets. Other hypotheses are raised by recent research, such as the potential influence of GenAI on *social relationships*, based on the finding that GenAI is increasingly used for drafting messages to other people [14] and for therapeutic dialogues [70]. Another avenue to explore is the impact of GenAI on *metacognitive evaluation*. Because cognitive offloading is influenced by metacognitive evaluations of what we believe ourselves capable to do, and because these evaluations can be erroneous, they can lead to suboptimal offloading behavior [54]. Such evaluations may be affected by reduction of an individual's self-efficacy. Recent studies have suggested that *technostress* caused by the pressure to adopt GenAI technology can have negative effects on an organization's performance (e.g., [42]), and if technostress perseveres, it is possible that it could negatively impact cognition.

6 Future perspectives

For each of the risk areas, it is essential to identify both *causes*, *moderating factors* and *effects (cost)*. For example, skill degradation as a consequence of cognitive offloading would likely be moderated by multiple factors. Some effects which may seem like a cost in short-term tasks may have no measurable impact on long-term cognition, and vice versa. Creating an in-depth contextual understanding of each of the areas of risk identified requires systematic qualitative and quantitative measurements of their impact on processes in practical work contexts. Even in the event of a zero-sum scenario where advantages will outweigh any adverse effects, the investigation of these risk areas will contribute to a comprehensive understanding of how the deployment of GenAI in knowledge work shapes the future of work, contributing to ethical and responsible interaction with GenAI in our lives and workplaces [16].

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