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Cognitive processes while using Artificial Intelligence at work: a research agenda on challenges and opportunities

Processi cognitivi nell'uso dell'Intelligenza Artificiale sul lavoro: un'agenda di ricerca su sfide e opportunità

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Abstract

The integration of artificial intelligence (AI) at work is transforming task execution, decision-making, and creative output, necessitating a deeper understanding of the users' cognitive processes involved. Following this endeavor, this paper proposes a comprehensive research agenda. First, its theoretical framework explores three established cognitive concepts linking them to human-computer interaction and information systems research. Second, it identifies key research themes and proposes methodologies to offer strategies to investigate these phenomena. Third, it highlights the potential of interdisciplinary research and thoughtful policies to ensure AI adoption aligns with human well-being, and ethical considerations. Ultimately, the insights motivate actionable strategies for organizations that ensure AI at work is designed in a human-centric way.

Keywords: AI; cognitive biases; cognitive load; creativity; human-centric design.

Sintesi

L'integrazione dell'intelligenza artificiale (IA) nei contesti lavorativi sta trasformando l'esecuzione dei compiti, i processi decisionali e quelli creativi, rendendo necessaria una comprensione più approfondita dei processi cognitivi degli utenti coinvolti. In questo senso, il presente articolo propone un'agenda di ricerca. In primo luogo, il quadro teorico esplora tre concetti cognitivi consolidati collegandoli alla ricerca sull'interazione uomo-computer e sui sistemi informativi. In secondo luogo, identifica i temi chiave di ricerca e propone metodologie per offrire strategie finalizzate all'indagine di questi fenomeni. In terzo luogo, evidenzia il potenziale della ricerca interdisciplinare e di politiche ben ponderate per garantire che l'adozione dell'IA sia in linea con il benessere umano, le considerazioni etiche e la sostenibilità. In ultima analisi, le intuizioni fornite motivano strategie praticabili per le organizzazioni, affinché l'IA nel lavoro sia progettata in modo centrato sull'uomo.

Parole chiave: IA; bias cognitivi; carico cognitivo; creatività; design centrato sull'uomo.

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1. Introduction

The increasing adoption of artificial intelligence (AI) is transforming workplaces across industries, fundamentally reshaping how employees perform tasks and interact with digital systems (Gorski et al., 2022; Mathiason et al., 2014; Vyas & Lilhore, 2023). From decision-support systems to generative AI (GenAI) tools, AI has become an integral part of organizational strategies aimed at enhancing efficiency, driving innovation, and sustaining competitive advantage around the globe. However, this shift comes with significant challenges. While AI technologies can automate routine processes, augment human capabilities and support efficiency, they can also introduce complexities in decision-making, problem-solving, and creative thinking. For information systems (IS) and human-computer interaction (HCI) research alike, understanding the interplay between these technologies and human cognition is vital for shaping the future of work.

The integration of AI tools into daily workflows can impact employees' cognitive processes in profound ways (Wilkens, 2020). They may reduce cognitive load by automating repetitive tasks, but also introduce new demands such as interpreting AI-generated insights, navigating algorithmic errors, and maintaining critical oversight without drawing biased conclusions (Howard, 2019). Misaligned systems can lead to unintended consequences, including fatigue, reduced acceptance of, or over-reliance on automation. Conversely, well-designed tools offer significant opportunities to enhance creativity, improve decision-making accuracy, and foster collaboration (Einola & Khoreva, 2023). For research and practice alike, these complexities raise important questions about how individuals adapt to AI-enhanced environments and how organizations can design AI systems that align with human cognitive capacities.

The question arises for both science and practice, on how companies can effectively implement human-centered AI (HCAI) (Passalacqua et al., 2024; Régis et al., 2024). HCAI focuses on designing AI systems that align with human needs and values, while upholding ethical and societal standards (Schmager et al., 2023). First, addressing this question requires a multidisciplinary approach that integrates cognitive science, systems design, and organizational strategy with HCI and IS research. Second, it demands the consideration of cognitive aspects of AI such as information-processing and decision-making. Third, regulatory frameworks play a key role. Policies such as the European *Artificial Intelligence Act* (EU AI Act) (European Commission [EC], 2024) and the European Commission's *Ethics Guidelines for Trustworthy AI* (EC, 2019) establish fundamental principles like transparency, safety, and human oversight to ensure AI supports rather than undermines human decision-making. While seeking to balance innovation and risk (EC, 2020), these regulations influence global discussions on AI adoption and use (Smuha et al., 2021). As AI reshapes life, businesses and policymakers need to prioritize human adaptability, cognitive resilience, and ethical responsibility. Against this background, we want to propose a research agenda that explores the cognitive challenges and opportunities associated with AI integration in the workplace. This paper aims to bridge critical gaps in understanding the cognitive implications of AI, providing a roadmap for future research and practical guidance for organizations navigating their AI journey. Because AI is profoundly altering cognitive processes and output expectations at the workplace, it is critical to understand how these changes impact human decision-making, creativity, and well-being. Addressing these shifts is essential for both science and practice to ensure that AI tools are designed to complement human capabilities rather than diminish them. Specifically, this paper seeks to:

- explore cognitive challenges arising from the use of AI tools, such as cognitive biases and cognitive overload;

- identify avenues where AI can enhance cognitive processes, such as creativity and decision-making;
- provide impulses on how to derive central research questions and study them methodically;
- offer preliminary strategic implications of AI adoption for organizations, including security, training, and policy design.

The article is structured as follows: Section 2 provides the theoretical background, illustrating cognitive processes in the context of AI technologies at work. Section 3 identifies key research themes and questions. Section 4 outlines proposed methodologies for studying these questions, highlighting mixed-method approaches. Section 5 discusses practical implications and insights for corporate strategy. The paper's limitations are highlighted in Section 6. Section 7 concludes with a call to action, emphasizing the importance of collaborative, interdisciplinary research to ensure AI systems are designed in a human-centric way.

2. Theoretical foundation

As AI technologies become increasingly embedded in the workplace, their impact on human cognition, information processing and corporate decision-making can be profound (Laird et al., 2017). This section explores the cognitive dimensions of human interaction with AI, grounding the discussion in well-established theories from cognitive science and psychology. By defining core concepts and linking them to frameworks from IS and HCI research, this section provides a foundation for understanding the transformative role of AI in the modern workplace. This sets the stage for the later research agenda.

AI refers to a technological system designed to simulate human intelligence, which is performing tasks such as learning from data, recognizing patterns, and solving problems (Howard, 2019). GenAI, a subset of AI, takes this capability further by creating new content, such as generating texts, images, videos, or audios, based on input data by using advanced algorithms like deep learning (Feuerriegel et al., 2024). Tools such as ChatGPT exemplify GenAI's potential to enhance work productivity. However, these technologies also introduce cognitive challenges that must be understood through a theoretical lens.

To frame this exploration, prominent concepts and theories are discussed to provide a solid foundation for understanding how individuals process information, make decisions, and engage in creative activities. Furthermore, a real-world example is integrated to highlight the practical implications.

2.1. Definition of core cognitive concepts

Successful AI adoption in modern organizations depends on aligning economic goals with human cognitive capacities, ensuring that technology enhances rather than overwhelms. Practice bears many examples that underline the need to study cognitive processes while using AI at work:

- creativity: the introduction of AI into marketing workflows may require designers to transition from the manual creation of content to the refinement of AI-generated outputs. This illustrates the need of examining the cognitive processes involved in human creativity when utilizing AI;

- cognitive biases: the application of AI-supported predictive analytics in finance can optimize cognitive effort by automating complex analyses, reducing the burden on human decision-makers. However, this reliance on technology can lead to cognitive biases, such as overconfidence, where users may place undue trust in AI-generated outputs without critically evaluating their validity. Furthermore, those insights may suffer from hallucinations (i.e. AI systems creating outputs that are nonsensical or inaccurate), generating plausible but incorrect information. Human oversight and comprehensive transparency are necessary to assess AI recommendations rather than accepting them uncritically;
- cognitive load: the deployment of AI-powered chatbots for customer support can automate repetitive tasks, reducing employees' workload. While beneficial in some cases, delegating tasks to AI may result in shallower processing of critical information by them, diminishing memory retention and leading to skill degradation over time. To mitigate this, continuous upskilling is essential to ensure employees retain problem-solving abilities and can effectively collaborate with AI (Zirar et al., 2023).

Figure 1 provides an illustration of the cognitive concepts mentioned.

Concept	*Definition*
Cognitive load (Grinschgl & Neubauer, 2022; van Merriënboer & Sweller, 2005)	Cognitive load refers to the amount of mental effort required to process information and complete a task. There are three types of load: • intrinsic load related to the inherent complexity of a task; • extraneous load imposed by how information is presented; • germane load as mental resources used to form and refine schemas. Cognitive offloading refers to the delegation of cognitive tasks to AI systems, allowing to focus on higher-order tasks with the risk of not mastering their own expertise.
Cognitive bias (Pessotto, 2017)	Cognitive biases are systematic deviations from rationality in judgment and decision-making caused by mental shortcuts or heuristics. Examples include: • over-reliance on AI-generated suggestions (automation bias); • interpreting information in a way that confirms pre-existing beliefs (confirmation bias).
Creativity (Feldon, 2007)	Creativity involves the generation of ideas or solutions that are novel, original, and appropriate for a given context. It involves divergent thinking, which emphasizes exploring many possible solutions.

Figure 1. Definitions of core cognitive concepts while using technology.

2.2. Theories on information processing and decision-making

Five theories form the foundation for the proposed research agenda exploring how humans interact with AI technology at work. These theories provide insights into understanding the cognitive processes involved, ultimately guiding the design of human-centric AI systems.

The information processing theory provides a fruitful starting point. It offers a basic framework for understanding how humans perceive, encode, store, and retrieve information (Bates, 2005; Loftus & Loftus, 2019). Its integration is relevant when studying cognitive processes in AI-mediated workplaces for several reasons. First, it emphasizes the sequential stages of information processing: by designing tools that align with these stages, organizations can ensure that users can efficiently interpret and utilize AI-generated outputs. This holds true for optimized interfaces for human perception, avoiding distraction to foster human attention, and to hide irrelevant data to optimize information retrieval. Second, the theory can support the examination of how employees interact with AI tools by highlighting bottlenecks, such as the limitations of working memory: pointing at the limited capacity of working memory is relevant to cognitive load management. Third, the approach offers insights into facilitating creativity, either by providing diverse suggestions to stimulate divergent thinking or by organizing outputs to support convergent thinking (Zhang et al., 2020). Overall, the information processing theory leads the way towards designing AI systems that not only complement human capabilities but also address cognitive limitations.

The dual-process theory describes two distinct modes of thinking (Sowden et al., 2018; Zielonka et al., 2024): System 1 is fast, intuitive, and automatic, whereas System 2 is slow, deliberate, and analytical. AI tools often simplify complex tasks, and encourage quick responses aligned with System 1. While this can save cognitive resources and time, it may also lead to a user's over-reliance on AI-generated suggestions if they trust the output without evaluation. In addition, tasks of high complexity and responsibility, demand analytical engagement associated with System 2. For instance, in crisis management or strategic decision-making, leaders must critically evaluate and refine ideas. Transparency, detailed explanations, or alternative scenarios are needed. This duality creates tension between AI automation (System 1), and the need for human oversight (System 2). Researchers are asked to identify optimal points where AI supports tasks while leaving room to human judgment.

The flow theory describes a state of deep focus and optimal engagement when individuals face tasks that balance challenge with their skill level (Csikszentmihalyi, 2014; Nakamura & Csikszentmihalyi, 2009). AI systems can either facilitate or hinder flow depending on their design and implementation. For instance, well-designed AI tools can offload mundane tasks (see 'extended mind theory'), allowing employees to focus on meaningful, intellectually stimulating activities that foster their creativity. Conversely, poorly designed tools can disrupt flow, reducing productivity and job satisfaction (Agarwal & Karahanna, 2000). The approach promotes deep engagement while using AI by dynamically adjusting task complexity, providing timely support, and minimizing distractions.

Prospect theory explains how individuals evaluate choices under conditions of risk and uncertainty (Dreher, 2007; Malecek & Schonberg, 2015). As AI systems frequently present recommendations, predictions, or decision options, they often involve trade-offs between potential gains and losses. Employees may interpret AI outputs differently based on how information is framed. Interfaces that present data in balanced and transparent ways can mitigate these framing effects and other cognitive biases. Thereby, AI tools encourage informed decision-making. By paying attention to framing, organizations can ensure that employees make decisions that are analytically sound, reducing the likelihood of errors driven by subjective perceptions of risk.

The extended mind theory posits that human cognition is not only confined to the brain but can be extended to external tools (Clark & Chalmers, 1998). This theory holds significant relevance in workplace settings that use AI, as its approach re-frames AI systems as extensions of human cognitive processes rather than mere tools. However, this integration introduces two challenges. First, while extending cognition can enhance task performance, it may lead to over-reliance on AI, diminishing individuals' ability to independently perform tasks. Second, the reliance on external systems for cognitive offloading can reduce memory retention, as users may process information less deeply. Nevertheless, the extended mind theory provides a valuable perspective for designing AI systems for workplace environments that integrate with human thought processes. By creating intuitive and supportive AI interfaces, organizations can empower employees.

The theories mentioned on information-processing and decision-making are summarized in Figure 2.

Theory	*Explanation*	*AI-related example*
Information processing theory (Payne, 1980; Simon, 1978)	The theory describes how humans encode, store, and retrieve information. It highlights the bottleneck effect, where limited working memory can hinder complex decision-making.	AI can serve as external memory to offload routine tasks, freeing cognitive resources for higher-order thinking.
Dual-process theory (Schneider & Shiffrin, 1977; Shiffrin & Schneider, 1977; Sloman, 1996)	The theory posits two systems of thinking: • System 1 is intuitive, fast, and automatic. It is often influenced by cognitive biases; • System 2 is deliberate, slow, and analytical. It is engaged when complex or unfamiliar problems require rational thought.	AI tools often trigger System 1 thinking due to their ease of use, but critical decision-making demands System 2.
Flow theory (Csikszentmihalyi et al., 2018; Nakamura & Csikszentmihalyi, 2009)	The theory refers to a state of deep engagement and immersion in tasks. Flow is achieved when challenges are balanced with skills and cognitive overload is avoided.	AI designed for creative tasks should support flow by offering optimal challenge levels and minimizing distractions.
Prospect theory (Kahneman & Tversky, 2013)	The theory proposes that decision-making involves two phases: • editing by framing and simplifying choices; • comparing options based on perceived gains or losses.	AI's ability to frame information impacts how humans perceive risks and benefits, influencing choices.
Extended mind theory (Clark & Chalmers, 1998)	This theory posits that cognitive processes are not confined to the brain but can extend into the environment using tools and artifacts. It further suggests that interactions with external objects can fundamentally shape the cognitive abilities, effectively blurring the lines between internal and external cognition.	Individuals can extend their cognitive capacity by integrating AI tools into their workflows. In this way, AI may support cognitive tasks by acting as an external extension of the mind.

Figure 1. Theories on information processing and decision-making.

2.3. Real-world evidence from a global leader

Accenture, a global leader in consulting and digital transformation, has heavily invested in technology to drive innovation and enhance workplace productivity (Frey, 2023; Harper, 2024). In 2024, Accenture's slogan, 'Human by Design' encapsulated its mission to integrate AI technologies in ways that amplify human potential. Through various applications, Accenture illustrates how concepts like cognitive load, cognitive biases, and creativity can be pragmatically addressed. While these efforts provide valuable insights, they also reveal the complexities and trade-offs involved in AI adoption, which may vary across cultural, organizational, and industry contexts. Surely, successful implementation of AI-driven decision-making is not universal. Differences in organizational readiness, data maturity, and regulatory environments can significantly impact outcomes.

First, Accenture uses GenAI to streamline complex tasks like content creation, software prototyping, and data analysis, leading to economic benefits (Marti, 2024). For example, teams working on digital marketing campaigns leverage GenAI to generate multiple creative variations of advertisements in real-time (Accenture, 2024b). This can reduce extraneous cognitive load by automating routine iterations, allowing employees to focus on germane cognitive load – refining and selecting the most effective designs. The outcome is an environment where cognitive resources are allocated to strategic thinking rather than repetitive tasks. However, as AI-generated outputs become more prevalent, there remains the challenge of ensuring that automation does not inadvertently reduce human expertise or creative intuition.

Second, recognizing the risks of automation bias, where users over-rely on AI-generated outputs, Accenture has implemented processes to maintain critical oversight. For instance, in project management tools enhanced by GenAI, employees are encouraged to validate AI-generated timelines and recommendations against historical project data (Accenture, 2024a). These measures align with the dual-process theory, ensuring that analytical System 2 thinking complements System 1's quick, intuitive assessments. Nonetheless, such reliance on data may introduce its own biases, reinforcing existing patterns rather than fostering adaptive, forward-looking strategies.

Third, one of the standout applications of GenAI at Accenture is in ideation workshops. Using AI to suggest novel ideas and solutions, teams combine divergent thinking (exploring multiple creative pathways) with convergent thinking (narrowing down to the best options). For instance, during a design-thinking session for a smart city project, GenAI can propose unconventional yet actionable ideas for urban energy management. By offloading routine brainstorming tasks, AI has the potential to free up participants to engage deeply in creative flow. However, the extent to which AI-generated ideas meaningfully contribute to innovation remains a question, particularly in creative industries where originality and contextual nuance are crucial.

Fourth, Accenture's AI-driven platforms also assist in strategic decision-making by aggregating and analyzing large datasets. For example, in client engagements, AI synthesizes market trends, customer feedback, and predictive analytics to provide actionable insights (Accenture, 2024a). By framing options and presenting trade-offs in a clear manner, this aligns with prospect theory, helping users evaluate potential gains and risks. This also means that Accenture's own employees are trained to interpret the output in a meaningful way and to spot biases. The company takes upskilling very seriously.

3. Key research themes and questions

The integration of AI technologies into the workplace brings about profound changes in how employees think, decide, and create. After the research gap and theoretical background have been discussed in the past two sections, the need for relevant research themes and questions arises. A research agenda that can be used to design organizational strategies and technological tools does not yet exist. As companies continue to invest in AI, this gap should be closed quickly, to align AI adoption in organizations with considerations about human cognition in a meaningful way. Thus, the following section provides a structured approach to exploring the cognitive implications of AI in the workplace. By investigating cognitive biases, cognitive load, and creativity, scholars and practitioners alike can thereupon develop actionable insights. The following Section 4 will then outline corresponding methodologies to investigate these phenomena.

3.1. Cognitive load, offloading and relief through AI tools

AI tools are often introduced in companies with the promise of reducing employees' cognitive load, yet their effects can be paradoxical. While automating repetitive tasks can alleviate extraneous cognitive load, poor system design or excessive information quantity can inadvertently increase effort. In a positive way, the tools can enable offloading, such as by using an AI-powered project management to track deadlines, allocate resources, and send reminders, allowing to focus on more creative or strategic activities. However, this behavior can hinder memory retention, skill development, or critical thinking. So, if employees consistently rely on AI (Schulz & Knierim, 2024), they might struggle to develop skills over time. Balancing these dynamics is crucial to maximizing the benefits of AI adoption.

Research questions:

- under what circumstances do AI tools alleviate cognitive load, and when do they exacerbate it?
- how do different user groups (e.g. novices vs. experts) experience cognitive load when using AI?
- how does cognitive offloading impact employees' long-term skill development in AI-supported workplaces?

3.2. Cognitive biases and AI decision-making

As employees interact with AI tools, cognitive biases can significantly influence decision-making. So far, research has concentrated on two distortions: automation bias and confirmation bias. Automation bias is perceived as the tendency to over-rely on AI-generated suggestions (Abdelwanis et al., 2024; Gafni et al., 2024) and can lead users to uncritically accept outputs without questioning their validity (Nissen et al., in press). Conversely, confirmation bias may cause users to selectively interpret AI recommendations to reinforce their pre-existing beliefs (Modgil et al., 2021). These challenges not only undermine the effectiveness of AI but also have potential implications for critical areas like resource allocation, hiring, or risk assessment.

Research questions:

- what conditions amplify or mitigate automation and confirmation biases when interacting with AI at work?
- how do user expertise and AI transparency impact the prevalence of biases?
- how do different AI design features (e.g., explanation mechanisms, feedback loops) influence the occurrence and mitigation of cognitive biases?

3.3. Creativity and AI-mitigated innovation

Generative AI is reshaping the creative landscape, impacting not only individual employees but also leadership approaches to innovation. While AI can enhance creativity by providing novel ideas, it may also lead to homogenization or dependency, where human input becomes secondary to AI outputs. Understanding this balance is critical for leveraging AI in creative industries and knowledge work.

Research questions:

- how does AI influence the creative processes of employees and leaders?
- in what ways does collaboration with AI differ from traditional human-only brainstorming?
- what strategies can be implemented to integrate AI into creative workflows without diminishing the value of human input?

4. Proposed research metodologies

To effectively study cognitive processes in AI-mediated workplaces, a range of research methodologies can be employed, each offering unique benefits and limitations. Thus, only employing multiple approaches ensures the understanding of how AI influences cognitive load, decision-making, and creativity while addressing practical challenges in real-world settings.

The reliability, validity, and objectivity of methods vary. Controlled experiments can offer high internal validity by isolating specific variables but may lack external validity. In contrast, ethnographic studies can provide rich, contextual insights with strong external validity but may be influenced by a researcher's biases, impacting objectivity. Self-reported measures, such as surveys, are efficient for capturing subjective experiences but may face challenges in reliability due to participant interpretation or bias. Only combining methodologies mitigates these challenges, enhancing overall generalizations. Triangulation increases the robustness of conclusions.

The resources required for these studies also differ. Experiments may demand specialized software, hardware, or lab environments, while case studies and ethnographic studies may require access to workplaces and significant time for prolonged observations. Surveys, though less resource-intensive, require substantial participant engagement. Longitudinal studies need various follow-ups for meaningful results. Aligning research questions with resource availability is essential to maximize the feasibility and impact of the proposed methodologies.

4.1. Research agenda for cognitive load while using AI

Understanding cognitive load and offloading while using AI is valuable for evaluating how effectively these technologies support or hinder human cognition. Measuring cognitive load requires diverse methodologies to capture mental effort, task complexity, and real-time challenges in human-AI collaboration. By following one of the four presented directions below, future researchers can gain a comprehensive understanding of how AI impacts workload and identify design improvements for human-AI interaction.

- workload analysis: studies can examine the complexity of tasks. For example, a workload analysis such as the Full Time Equivalent method (Dahlan et al., 2021) can explore how much responsibility and time effort shifts from employees to AI in decision-making tasks. Next, it can be investigated whether this redistribution genuinely reduces the employees' overall cognitive effort or merely transforms it into a different type of cognitive demand, such as interpreting AI outputs;

- ethnographic studies: observing employees in their natural work settings can uncover nuanced individual cognitive challenges that emerge during AI usage. Ethnographic approaches allow researchers to capture real-time behaviors, strategies, drivers, and challenges (Denzin & Lincoln, 2016; Hoholm & Araujo, 2011) as employees engage with AI tools. For example, such studies can identify whether employees experience cognitive overload when switching between multiple systems or if they develop adaptive strategies to mitigate fatigue;
- assessments of cognitive load: tools such as the NASA Task Load Index (NASA-TLX) provide self-reported metrics of perceived mental effort (Hart, 2006), allowing researchers to quantify how AI tools influence workload during specific tasks. By offering additional objective insights, physiological measures, such as eye-tracking, heart rate variability, or electroencephalography (EEG), can complement subjective assessments. For instance, monitoring gaze patterns can reveal how users process AI-generated output or struggle with poorly designed interfaces;
- assessments of cognitive offloading: externalization to AI tools might affect cognitive performance both positively and negatively. Methodologies like the Color Block Test and the Digit Recall Tests can be used to measure how well people perform tasks and retain information when executing offloading (Tarde & Joshi, 2023). Furthermore, behavioral tracking methods, such as monitoring the frequency of external aid or task-switching patterns, can offer insights. Combining these methods with advanced objective data collection techniques, such as eye-tracking (Gauselmann et al., 2023) or EEG (Ritz et al., 2024) can provide real-time information on the benefits and drawbacks of cognitive offloading;
- longitudinal studies: panels can provide valuable insights into how AI systems affect cognitive offloading over time. These long-term studies can track whether AI tools consistently reduce cognitive load or unintentionally shift it, such as by creating new demands in interpreting or validating AI outputs. Monitoring employees over months or years can reveal whether frequent offloading becomes habitual or if individuals develop strategies to manage their cognitive effort effectively. These studies are also valuable for identifying cumulative effects on memory retention, adaptability, and skill erosion across different career stages, offering insights into how AI can shape cognitive processes over time.

4.2. Research agenda for cognitive biases while using AI

Cognitive biases, such as automation bias and confirmation bias, are critical factors influencing how employees interact with AI systems. Measuring these biases involves a combination of experimental, observational, and perceptual methodologies to uncover how biases arise and work. Mixing the methodologies presented below, provides a robust framework for assessing biases in AI interaction, enabling researchers to design interventions that mitigate unintended consequences of AI adoption:

- experimental studies: controlled experiments allow researchers to simulate decision-making scenarios where participants interact with AI tools under varying conditions. For instance, one can examine whether increasing the explainability of

AI outputs reduces automation bias, or if presenting alternative perspectives mitigates confirmation bias. Such experiments can provide valuable insights into how design features affect bias prevalence and decision quality;

- case studies: real-world case studies delve into how cognitive biases manifest within organizations. These studies can uncover patterns of over-reliance on AI outputs, offering practical insights for refining AI systems and AI-mitigated workflows. In the beginning, such investigations might focus on critical tasks such as hiring, promotion, or risk assessment;
- surveys: questionnaires are a widely used method to capture perceptions of AI reliability (Kashive et al., 2020; Shinners et al., 2021). They explore how users perceive the accuracy of AI-generated insights, their confidence in making judgments, and their inclination to critique or accept recommendations. In the future, they may go hand in hand with structured interviews of individual stakeholders or focus groups.

4.3. Research agenda for creativity while using AI

Measuring creativity while using AI, particularly GenAI, requires methodologies that capture both subjective experiences and objective outcomes of creative processes. By leveraging these approaches, future researchers can better understand how AI reshapes creativity in the workplace and identify ways to design systems that foster, rather than constrain, human ingenuity:

- interviews: qualitative interviews with employees and leaders can provide insights into their experiences with and opinions about AI usage during creative tasks. They can uncover how technology inspires ideas, streamlines ideation, or potentially limits originality. For example, designer teams might be invited to evaluate whether AI-generated suggestions expand their creative boundaries;
- longitudinal studies: examining the long-term impact of AI on creative output helps to determine whether AI consistently enhances originality or causes gradual dependency. These studies can track projects over time, evaluating whether teams might excel, plateau or fall short in technology-mitigated creative processes. Prolonged exposure to AI systems might lead to dependency, deskilling, or diminished critical thinking (Savin et al., 2024). Studies are needed to investigate how AI affects employee cognition, skill retention, and innovation capacity over time. So far, many promising studies focus on short-term effects of AI on cognitive processes (Haider et al., 2024), overlooking long-term implications;
- comparative analyses: to isolate AI's influence, researchers can compare creative performance between teams using AI tools and those relying solely on human ideation. Metrics like the novelty and feasibility of solutions can highlight differences in creative outcomes and reveal whether AI serves as an enabler or merely a facilitator. Collaborative scenarios can ultimately foster the understanding on how teams collectively process, share, and retrieve information, which can then help optimize the design of collaborative AI tools and workflows.

5. Implications for practice and policy

As companies continue to invest in AI, aligning AI implementation with cognitive considerations will be essential for maximizing organizational and employee performance.

The integration of AI into workplaces, particularly GenAI, has far-reaching implications for organizational, governmental, and ethical policy frameworks.

5.1. General implications for practice

By considering the frameworks presented in Section 2, companies can better align their AI adoption strategies with their employees' capacity, fostering environments where AI enhances productivity, creativity, and well-being. Several key implications emerge for designing and deploying AI systems in practice.

First, organizations need to prioritize AI system designs that reduce extraneous cognitive load and support germane cognitive load. For example, automating low-complexity tasks allows employees to allocate mental resources to strategic, creative, or analytical tasks. To achieve this, AI interfaces should provide concise information and intuitive navigation, minimizing unnecessary effort. Regular usability testing can help identify challenges. On top of that, organizations are asked to proactively assess the cognitive impact of AI tools on employees to prevent overload and fatigue. Periodic surveys, workload analyses, and feedback sessions can help. AI strategies must then include regular assessments of employees' mental health, particularly in cognitively demanding roles. Additionally, providing training on effective AI usage and setting realistic expectations can empower employees to manage their workload better. Workplaces can provide resources and integrate AI systems with tools that monitor and support well-being, such as digital assistants offering personalized task management or stress reduction tips.

Second, organizations need to carefully manage cognitive offloading to balance its benefits with the potential risks. AI tools should integrate features that occasionally prompt users to engage in tasks manually, reinforcing memory and problem-solving skills. Similarly, training programs should help employees develop strong metamemory, i.e., an awareness of when and how to rely on offloading, ensuring they use AI tools strategically without compromising their long-term abilities. These ideas will help leverage offloading benefits while preserving employees' core skills and capacity.

Third, AI tools should be designed to balance the complexity of tasks with employees' skill levels, fostering states of deep engagement, or flow. For instance, AI systems that gradually increase task complexity as user expertise grows can maintain motivation. This is particularly crucial in roles requiring innovation and strategic problem-solving, where flow states enhance both performance and satisfaction.

Fourth, AI systems should include features that encourage critical evaluation of outputs to counter cognitive biases. For example, providing explanations for AI-generated recommendations and offering alternative options can support informed decision-making. Training programs that teach employees to question and verify AI outputs can also promote critical oversight and reduce reliance on automated suggestions.

Fifth, GenAI tools should be implemented as collaborative partners rather than replacements for human creativity. Organizations can integrate these tools into workflows that encourage brainstorming and idea refinement. For example, using AI to generate initial concepts while relying on human teams for final creative decisions ensures that AI supports rather than stifles innovation.

Summing up, regular feedback loops can ensure that systems evolve to meet user needs. Employees should have channels to report usability issues, cognitive challenges, and suggestions for improvement. This iterative approach helps organizations adapt AI systems to dynamic environments and demands. By implementing these strategies, organizations can create AI systems that align with human cognitive capacities, promote employee engagement, and support broader goals of innovation and competitiveness.

5.2. Specific implications for policy

Addressing central cognitive dimensions of AI usage, cognitive load, cognitive biases, and creativity, can guide corporate strategists in creating regulations and guidelines that promote equitable, productive, and sustainable AI adoption.

First, policies should mandate that AI tools used in workplaces prioritize human-centered design principles, prominently those adhered with HCAI. These principles include transparency, explainability, and adaptability to mitigate cognitive biases and reduce cognitive overload. Regulatory bodies could establish guidelines for AI interface design, ensuring that systems present information in ways that enhance critical thinking, avoid over-reliance, and reduce stress. Moreover, policies should require regular bias audits in decision-making processes, such as hiring, performance reviews, or resource allocation. Transparent reporting and accountability mechanisms can help organizations identify and address biases that may inadvertently impact fairness and equity. Additionally, cognitive offloading requires careful regulation. Policies should encourage designs that balance offloading benefits with skill retention, ensuring employees remain engaged. Organizations should adopt guidelines to monitor offloading behaviors responsibly. Furthermore, the European Commission's regulatory frameworks provide a foundation for ensuring AI systems are designed to complement human cognition rather than diminish it. For instance, the EU AI Act categorizes high-risk AI applications and mandates stringent compliance measures, reinforcing the importance of accountability in AI-driven workplace environments. Aligning workplace AI regulations with these frameworks can help safeguard employee autonomy while maintaining the benefits of automation.

Second, strategists should advocate for AI literacy programs that equip employees with the skills needed to critically evaluate AI-generated outputs. Training initiatives should address common biases, decision-making pitfalls, and guidelines for effective human-AI collaboration. Funding or incentives for such programs could encourage widespread implementation across industries.

Third, policies must address the balance between AI-enabled innovation and the protection of human creativity. For instance, organizations could be required to report on the originality of AI-influenced creative outputs to ensure that AI augments rather than diminishes human ingenuity. Intellectual property laws may need updating to address ownership of AI-generated ideas or designs. In addition, given the data-intensive nature of AI systems, policies must ensure robust protections for employee data privacy. This includes establishing clear boundaries for how AI systems can monitor and analyze cognitive processes, ensuring that data collection is consensual and minimally invasive. In the same way, policies should draw on the concept of AI safety from the users' perspective.

Fourth, policymakers need to address the significant energy consumption and environmental impact of AI, particularly large-scale GenAI models. Organizations should be incentivized to adopt energy-efficient AI architectures and utilize renewable energy sources for their computational needs. Transparent reporting on the carbon footprint of AI operations should be mandated to align with broader sustainability goals.

In sum, corporate strategists should encourage collaborations between scientists, AI developers, and organizational leaders to create AI systems that align with human cognitive capacities. Incentives for interdisciplinary research can pave promising ways to address the complex interplay of AI and cognition, fostering responsible and effective innovation.

5.3. Targeted implications for a global leader

Section 2.3. presented Accenture's significant investment in GenAI and AI-driven technologies. Its investments position the company as a leader in reshaping workplaces and driving innovation. To maximize the potential of AI tools while ensuring employee well-being, the recommendations for practice are now tailored to Accenture's context.

Accenture should emphasize designing client-facing AI tools that reduce extraneous cognitive load for users. This can include intuitive dashboards, clear visualizations, and context-sensitive explanations for AI-generated insights. These features will help clients focus on germane cognitive activities, such as strategic planning or innovation, enhancing the value of Accenture's services. Given Accenture's role in deploying AI for clients, the company should also embed bias mitigation features into its AI solutions. For example, decision-support tools could include counterfactual explanations or alternative scenarios to reduce automation bias. Training client teams to critically evaluate AI outputs will ensure informed decision-making across industries. In addition, features that balance cognitive offloading, like requiring manual engagement for certain tasks, can prevent over-reliance on AI tools. Training programs for clients should incorporate guidance on strategic offloading, such as performing periodic manual validations, to ensure AI augments their capabilities without eroding key skills.

For Accenture's own employees, integrating AI systems that balance complexity with skill level can enhance flow and engagement. AI tools should ensure tasks remain both challenging and manageable. This can foster deeper immersion, especially for consultants in high-pressure roles. These consultants often work on demanding projects requiring rapid adoption and adaptation. To prevent burnout, Accenture can implement periodic cognitive load assessments using tools like the NASA-TLX. To support employee well-being, Accenture can integrate tools that assist with prioritization, stress management, and workload distribution. For example, deploying digital assistants to help consultants manage their schedules and focus on high-priority tasks can alleviate stress. Finally, Accenture should continue its investments in AI literacy programs for employees at all levels, ensuring equitable access to AI tools. Tailored training sessions for consultants and client teams can promote confident and ethical use of AI, enhancing adoption and impact across projects. Offering training can further mitigate cognitive strain.

Co-creative teams and innovation hubs with both Accenture and client employees can benefit from AI as a collaborative partner. AI tools can generate initial ideas for product design, service models, or marketing strategies, while humans refine and finalize solutions. This approach ensures that AI enhances creative workflows without overshadowing human input. In these co-creative teams, leaders should formalize feedback loops between its employees, clients, and AI development teams. For instance, consultants and client users could report usability challenges or cognitive barriers through structured surveys. This iterative feedback process will enable developers to refine AI systems continuously and maintain alignment with user needs.

6. Limitations and omitted future research directions

Building upon the existing research agenda, several additional considerations and directions for exploration emerge to address the complexities of AI in the workplace.

This article offers a practical approach with a real-life case study to derive promising research questions that are relevant for both science and practice. However, we recognize the lack of a systematic literature review for our endeavor. Since the field of HCAI is still new, a systematic literature review will help identify additional knowledge gaps and provide a stronger theoretical foundation. In the future, we plan to combine the two views by reviewing recent studies from leading conferences like CHI and ACM HCI. This will allow us to build a more comprehensive research agenda that bridges the theoretical and practical aspects of this emerging field.

One challenge remains in accurately assessing cognitive impacts, such as cognitive load, cognitive biases, and creativity. The discussed methodologies may lack scalability or fail to capture nuanced, real-time interactions with AI systems. In addition, tasks to measure creativity or learning, which rely on tacit knowledge, are difficult to evaluate. Future research should explore advanced tools like AI-driven analytics to enhance measurement precision. Another challenge concerning measurement is that collecting data on cognitive processes while using AI may raise ethical questions about privacy, consent, and potential misuse. For instance, monitoring employee behavior to assess cognitive load could be perceived as intrusive. Future work should address how organizations can balance data collection with ethical considerations, ensuring transparency and agency.

It is important to note that this article focuses only on two out of many cognitive biases. It does not address potential biases related to gender and ethnicity, inherent in some of the training datasets used. The authors are aware that these biases can significantly lead to system-based inequities if not critically evaluated. Future work should explore the academic discussion of these biases and further mitigation strategies (Barocas et al., 2017).

Another shortcoming of the paper is that the cognitive impacts of AI adoption are likely to differ across cultural, organizational, and industry contexts, which was not yet considered. Perceptions of or trust in AI may vary based on cultural norms. Future studies should explore how these contextual factors shape cognitive responses to AI systems. Looking at real-world implications, scalability remains an issue. While upskilling initiatives are essential, scaling these programs across multiple organizations and industries bears logistical and financial costs. Future studies should explore scalable AI literacy programs, including virtual training platforms or gamified learning experiences that accommodate different learning styles and skill levels. Future work should also investigate how to balance efficiency gains with upskilling, particularly in industries heavily reliant on innovation. Additionally, beyond current initiatives, organizations must anticipate future cognitive demands posed by emerging AI technologies. This includes preparing employees for adaptive thinking and problem-solving in rapidly evolving AI environments. Organizations need to focus on developing frameworks for continuous learning that align with the pace of technological advancement.

Focusing on future research directions, there is a need for interdisciplinary collaboration between fields such as cognitive science, organizational psychology, and data science with IS and HCI. Interdisciplinary approaches can provide more holistic insights into the interplay between AI technologies and cognitive processes, addressing gaps that isolated disciplines might overlook. An interesting avenue is the fact that AI adoption influences not only individual cognition but also collective processes like team collaboration, communication, and shared decision-making. Future research is invited to investigate how AI alters team dynamics, particularly in hybrid human-AI teams, and identify strategies to optimize these interactions.

By addressing these limitations and pursuing these research directions, organizations and researchers can better navigate the challenges of AI adoption, ensuring that its integration into workplaces supports both human potential and organizational goals.

7. Conclusions

The integration of AI in workplace environments presents both opportunities and challenges. This article has outlined a multidisciplinary research agenda to address the cognitive implications of AI adoption at work, emphasizing the importance of aligning technological design with human capacities. By leveraging established theoretical frameworks and exploring research themes such as cognitive load, cognitive biases, and creativity, the paper provides a foundation for advancing studies on HCAI systems that complement rather than hinder human abilities.

For practitioners, the paper underscores the necessity of designing adaptive AI systems that foster productivity while safeguarding responsibility. For researchers, the outlined methodologies offer pathways for investigating the interplay between AI and human cognition, especially encouraging mixed-method and interdisciplinary studies, advocating for collaborative effort. Finally, the work highlights the need for corporate strategy that promote human well-being, ethical practices, security, and sustainability. By adopting an evidence-based approach to AI integration, organizations can unlock new opportunities for innovation and thoughtful decision-making, especially in a rapidly evolving world.

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