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Human-AI agency in the age of generative AI

Sebastian Krakowski *

House of Innovation, Stockholm School of Economics, Sweden

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ABSTRACT

The rapid emergence of generative artificial intelligence (GenAI) is profoundly transforming the nature of work and organizations, challenging prevalent views of AI as primarily enabling prediction and optimization. This paper argues that GenAI represents a qualitative shift that necessitates a fundamental reassessment of AI's role in management and organizations. By identifying and analyzing four critical dimensions — (i) GenAI's broad applicability as a general-purpose technology; (ii) its ability to catalyze exploratory and combinatorial innovation; (iii) its capacity to enhance cognitive diversity and decision-making; and (iv) its democratizing effect on AI adoption and value creation — the paper highlights GenAI's potential to augment and scale human creativity, learning, and innovation. Building on insights from the AI and management literature, as well as on theory of human-AI agency, the paper develops a novel perspective that challenges the dominant efficiency-oriented narrative. It proposes that a human-complementary approach to GenAI development and implementation, leveraging it as a generative catalyst for exploration, can enable radically increased creativity, innovation, and growth. GenAI's democratizing aspects can amplify these mechanisms, promoting widely shared growth when combined with appropriate policy and managerial choices. Implications for theory, practice, and future research directions are discussed, drawing attention to the need for approaches in GenAI development and deployment that are complementary rather than competitive to human beings. The paper concludes by discussing the theoretical, practical, and policy implications of this transformative technology. It outlines future research directions, emphasizing the critical role of human agency in determining the organizational, societal, and ethical outcomes associated with AI adoption and implementation.

1. Introduction

The rapid advancement of artificial intelligence (AI) is profoundly transforming organizations and the nature of work in ways that can be likened to the impact of electrification on factories during the industrial revolution (Agrawal, Gans, & Goldfarb, 2022). Just as electricity empowered people to work more independently and take on more autonomous, value-creating initiatives, AI is expected to enable innovation on a distributed scale by giving employees access to information-processing and reasoning capabilities. Research on AI in management has explored its impact on organizations, focusing on AI adoption approaches and the division of labor between human and AI agents (Choudhary, Marchetti, Shrestha, & Puranam, 2025; Raisch & Krakowski, 2021; Shrestha, Ben-Menahem, & von Krogh, 2019). The emergence of generative AI (GenAI) has however marked a significant leap beyond the capabilities of predictive AI, which primarily enabled automation and analytical decision support, with early findings indicating GenAI performance reaching or

* Corresponding author.
E-mail address: sebastian.krakowski@hhs.se.

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even exceeding human performance in tasks involving divergent thinking (Hubert, Awa, & Zabelina, 2024), social intelligence (Sufyan, Fadhel, Alkhathami, & Mukhadi, 2024), and empathic communication (Yin, Jia, & Wakslak, 2024), among others.

Despite these advancements in capabilities, as well as indications that GenAI is being adopted at rates comparable to (or even exceeding) prior emerging transformational technologies like the PC, the internet, and prior AI iterations (Bick, Blandin, & Deming, 2024; Humlum & Vestergaard, 2024; Wu et al., 2023), the dominant discourse in AI and management research still primarily frames AI as a tool for uncertainty mitigation and operational efficiency (Constantinides, Monteiro, & Mathiassen, 2024; Jarrahi, 2018). GenAI challenges this prevalent view, as its value and impact largely relate to its generative nature, widespread accessibility, and associated capacity to generate novel and creative output (Adam, 2023; Davenport & Mittal, 2022; Epstein et al., 2023). Current theory and assumptions relating to human-AI collaboration are based on the capabilities of predictive AI and do not adequately address how humans can be expected to interact and work with GenAI, representing a fundamental and qualitative shift that implies a reassessment of AI's potential and desired impact in organizations and society.

Neglecting GenAI's transformative aspects in academic conceptualization and contemporary discussion constrains our understanding of its implications for management theory and practice. Being limited to considering AI's predictive and optimizing capabilities in a convergent logic – characterized by efficiency, accuracy, and optimization (Amabile, 2020; Cabantous & Gond, 2011) – prevents current frameworks from fully capturing GenAI's impact on not only convergent tasks, but particularly divergent tasks involving creativity and innovation. These may prove to be essential drivers of individual and organizational performance, societal progress, and economic growth. This narrow focus impedes the development of theoretical models and practical strategies that can guide organizations in leveraging GenAI to augment human potential and drive value creation. The inadequate consideration of GenAI's unique characteristics and transformative potential needs to be addressed to advance our understanding of AI's role in management and organizations.

This paper uses innovation search as an analytical lens to develop four key propositions that suggest a foundational reassessment of AI's role in management and organizations: (i) GenAI's broad applicability as well as its generalizable reasoning and learning capabilities distinguish it from predictive AI across both divergent and convergent applications in tasks, effectively contributing to making AI a general-purpose technology (GPT); (ii) building on its capabilities and wide applicability, GenAI's generative capabilities enable a shift from exploitative to exploratory uses in both problem definition and solution search stages, catalyzing innovation through recombining concepts and ideas; (iii) as such, GenAI can act as a complementary artifact that augments human learning, creativity, and innovation throughout the problem-solving process; and (iv) GenAI's affordability, accessibility, and conversational interfaces democratize AI adoption across organizational tasks and contexts, amplifying and compounding the speed and impact of these propositions.

By identifying and analyzing these dimensions, this paper makes three main contributions. First, it challenges the dominant efficiency- and convergence-oriented narrative in AI management literature by demonstrating how GenAI enables both divergent and convergent applications in problem solving. Second, it advances theory on human-AI hybrid agency by examining how GenAI's distinctive capabilities affect task allocation and interdependencies between human and artificial agents in the problem definition and solution search stages of problem solving. Third, adopting a task-based perspective of the impact of technology on the economy, labor, and organizations, it provides insights for policy and practice. The paper develops these arguments through theoretical background, analyzing the main dimensions and discussing implications, whereafter it concludes with directions for future research on GenAI's impact on humans, organizations, and society.

2. Background

AI overview. AI refers to machine agents that "perform cognitive functions that we associate with human minds, such as perceiving, reasoning, learning, interacting with the environment, problem solving, decision-making, and even demonstrating creativity" in pursuit of goals (Rai, Constantinides, & Sarker, 2019, p. iii). Unlike past transformative technologies such as steam power and electricity, which primarily enabled humans to overcome physical limitations, AI allows humans to perceive and process information at an unparalleled, often superhuman level (Brynjolfsson & McAfee, 2014, p. 91f).[1]

AI's early development focused on symbolic approaches that relied on explicit logic and representation of problems and knowledge. These methods faced limitations in representing and processing the extensive knowledge required for general intelligence. In more recent years, there has been a shift toward statistical approaches, primarily using machine learning (ML), particularly deep learning (DL), that enables more complex neural networks and more highly performant AI algorithms, to inductively infer rules from data (Russell & Norvig, 2020, p. 17ff). AI's rapid proliferation is largely driven by ML-enabled "predictive AI," which "learns patterns from existing data to anticipate future outcomes" without explicit human-encoded rules (Raisch & Fomina, 2025, p. 2), including "discriminative AI" used for classification purposes (Berg, Raj, & Seamans, 2023, p. 425). This progress is generally attributed to three key factors – the growth of available data, the increased processing power of computing hardware, and the development of sophisticated algorithms that require less data to accomplish the same level of performance (Brynjolfsson & McAfee, 2017). Their

[1] Although the AI field includes many hardware-oriented subfields, particularly robotics and other embodied agents, this paper limits its scope to software-based approaches. Computationalism, which views intelligence as pure information processing, may provide an incomplete perspective on AI (e.g., Putnam, 1988). For instance, embodiment and qualia may be requirements for intelligence. This paper adopts a phenomenological conceptualization of intelligence that extends to demonstrated capabilities of distinct (hybrid) agents, as opposed to collective or cumulative notions of intelligence such as culture (e.g., Migliano & Vinicius, 2021).

convergence has enabled AI to achieve human-level performance[2] in tasks such as recognizing handwriting, images, and speech, as well as natural-language understanding. While the trajectory and ultimate potential of DL-based approaches is subject to debate (Marcus, 2022), the rate of improvement in AI capabilities is expected to remain steady or even accelerate in the coming years (Henshall, 2023, 2024).

GenAI represents a significant advancement in AI, constituting an ML subset that "creates new data based on learned patterns" (Raisch & Fomina, 2025, p. 2) through probabilistic sampling mechanisms (Noy & Zhang, 2023). The most flexible and highly performant of these general-purpose systems known as "foundation models" – including ChatGPT (OpenAI), Claude (Anthropic), Copilot (Microsoft), and Gemini (Google) – are trained on large-scale multimodal datasets, enabling them to process and generate content across diverse formats, such as text, audio, images, and video. This scale allows high performance on a wide array of tasks and leads to emergent capabilities beyond their explicit training objectives (Bommasani et al., 2022; Cillo & Rubera, 2024).

Large language models (LLMs), a prominent category of GenAI, specialize in natural-language processing and generation. These systems "are trained on string prediction tasks: that is, predicting the likelihood of a token (character, word or string) given either its preceding context or … its surrounding context" (Bender, Gebru, McMillan-Major, & Shmitchell, 2021, p. 611). They produce text that closely mimics or is even indistinguishable from human writing in terms of perceived provenance and utility (Fleckenstein et al., 2024). The training process typically involves fine-tuning through human-annotated datasets and may also use task-specific data to optimize domain-specific responses. LLMs generate output by selecting the next token (a subword unit of text) from a probability distribution of likely tokens based on human input. This approach enables the models to balance generating common or highly probable text with more divergent or creative outputs – a balance a human can adjust by modifying hyperparameters that influence the sampling mechanism (Bellemare-Pepin et al., 2024; Boussioux, Lane, Zhang, Jacimovic, & Lakhani, 2024).

Current perspectives on hybrid agency. The fields of organizational theory and AI share many foundational conceptualizations of agency,[3] particularly regarding agentic information processing in pursuit of goals.[4] Both disciplines are concerned with how agents or systems, whether human organizations or AI systems, can engage in intelligent,[5] goal-oriented behavior where multiple agents or subsystems can be combined and coordinated to accomplish stated objectives (Choudhary et al., 2025; Csaszar & Steinberger, 2022). The rapid proliferation of AI in organizations has led to a growing academic interest in the concept of *hybrid* (or *conjoined*) *agency* between humans and AI systems, referring to the capacity of humans and AI to jointly engage in goal-oriented behavior (Krakowski, 2020; Murray, Rhymer, & Sirmon, 2021). This agentic view of AI emphasizes the importance of considering its consequences on work practices and the associated need for novel organizational structures and processes (Anthony, Bechky, & Fayard, 2023). Given that AI technologies can process large amounts of data, acquiring human-level cognitive abilities and knowledge, and can operate autonomously, they differ fundamentally from prior technologies in their ability to shape and constrain human and organizational behavior (Berente, Gu, Recker, & Santhanam, 2021; Rahwan et al., 2019).

With human-AI collaboration, *automation* and *augmentation* are key concepts in understanding hybrid agency (Raisch & Krakowski, 2021). Automation involves AI systems taking over tasks that humans previously performed, while augmentation describes the collaboration between humans and AI in completing tasks. These concepts are interdependent and form a cyclical relationship where task augmentation may enable its automation, which can trigger further augmentation in related tasks. As AI technologies become more autonomous, organizations are adopting different approaches to manage these forms of hybrid agency, striving to combine and integrate human and AI strengths over time (Choudhary et al., 2025; Shrestha et al., 2019). This shift implies that the role of humans in decision making is gradually moving away from operational tasks toward higher-order ones such as problem identification, goal setting, and configuring systems that enable AI to act autonomously (Verganti, Vendraminelli, & Iansiti, 2020). This transition requires humans to develop new capabilities that are distinct or even orthogonal to conventional resources and skills (Krakowski, Luger, & Raisch, 2023).

While acknowledging critical perspectives on AI adoption, such as the risk of decreasing human agency through disengagement, deskilling, or resignation (den Hond & Moser, 2023; Lindebaum, Moser, & Islam, 2024), the opportunities afforded by human-AI agency hold considerable promise. Studies have found that AI can improve efficiency and profitability, enable humans to focus on more value-adding or rewarding tasks, and address problems previously unattainable by humans or AI in isolation (Hartmann & Henkel, 2020;

[2] Artificial general intelligence (AGI), sometimes used interchangeably with human-level AI (HLAI), is typically defined as AI that can perform a wide range of tasks at a level comparable to humans (Goertzel, 2014; Morris et al., 2024). Present-day AI models are considered *narrow AI* due to their proficiency in limited and specialized tasks. There is debate about when, or indeed if, an AGI system will be realized, although GenAI models are considered an important step toward this objective (Bubeck et al., 2023; Roser, 2022). Given the dynamic and complementary nature of human and artificial capabilities that vary across tasks and contexts (Lawrence, 2024, p. 28f), this paper aligns with the position that building a superior AI system across diverse tasks remains unlikely in the near future.

[3] *Agency* is defined as the capacity of a biological or artificial entity to act toward goals based on decision-making processes that use feedback to adapt behavior and achieve desired outcomes (Tomasello, 2022, p. 11ff). This process is problem-driven or problemistic, with agents modifying their actions in response to feedback and adjusting their approach based on learning (Cyert & March, 1963; Gavetti et al., 2012).

[4] These goals may be conflicting or temporally unstable, and technologies like AI are typically developed to support and enhance human agents in this goal-oriented search process (March, 2006).

[5] *Intelligence* refers to an agent's ability to engage in adaptive search behaviors that identify and pursue actions aimed at achieving stated goals (Chollet, 2019). In this context, intelligence is seen as a capacity of individual agents as well as a context-dependent phenomenon shaped by both the structure of task environments and an actor's computational capabilities, functioning like "a scissors" (Simon, 1990, p. 7). In this paper, intelligence is conceived as a multidimensional construct that exhibits "competitive intransitivity" (Lawrence, 2024, p. 28f), where strengths in one domain do not imply dominance across others. This perspective emphasizes that human and artificial intelligence are temporally and contextually dependent, lacking any linear or stable hierarchy.

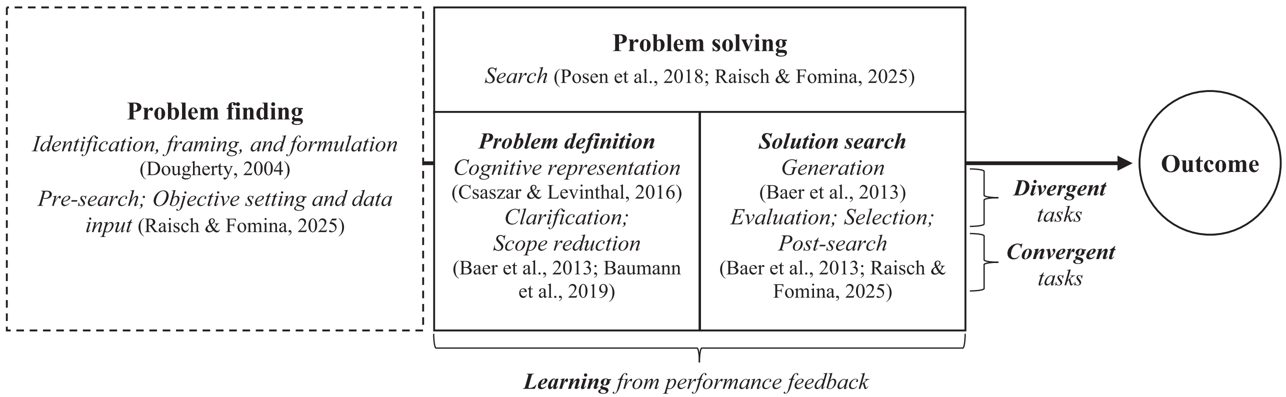

Fig. 1. Innovation search as a theoretical lens.

Wang, Gao, & Agarwal, 2024). As AI capabilities expand into exploratory tasks and creative problem solving through GenAI (Kulkarni et al., 2024), it represents a new frontier of human-AI agency that requires theoretical and practical consideration (Amabile, 2020).

This paper argues that current research in AI and management predominantly conceptualizes AI in a paradigm focused on uncertainty reduction and optimization, and frame human-AI agency as a comparatively static organizational design choice. This calls for an extension of current theorizing as well as practice that accounts for the cyclical dynamics of AI automation and augmentation (Raisch & Krakowski, 2021), with explicit consideration of current and emergent capabilities associated with GenAI as a technology (Bubeck et al., 2023; Roser, 2022).

Innovation search as a theoretical lens. To develop its arguments, this paper assumes an organizational search perspective, adopting a problem-finding and problem-solving lens of strategy, innovation, and entrepreneurship (Felin & Zenger, 2016; Newell & Simon, 1972). In line with this literature, the framework in Fig. 1 depicts innovation as a search process where organizations navigate problem spaces to generate novel solutions (Dahlander, O'Mahony, & Gann, 2016; Katila & Chen, 2008).

Problem finding. Also referred to as for example *problem formulation* or *idea finding* (Abdulla & Cramond, 2018), problem finding is defined as "a collective activity aimed at translating an initial problem symptom or web of symptoms into a set of questions or alternative formulations … to enable the subsequent search for or generation of solutions." This differs from *problem solving*, which "comprises the generation, evaluation, and selection of alternative solutions" (Baer, Dirks, & Nickerson, 2013, pp. 197–198). Drawing on Raisch and Fomina's (2025) framework of "hybrid problem solving" (building on Posen, Keil, Kim, and Meissner's (2018) conceptualization of problem solving as search), Fig. 1 depicts the innovation search process in three phases: *problem finding, problem solving* (encompassing *problem definition* and *solution search*), and *outcome*.

The initial phase, problem finding, involves tasks such as problem identification, framing, and formulation (Dougherty, 2004; Nickerson, Yen, & Mahoney, 2012). This phase also subsumes the *pre-search* stage from Raisch and Fomina's (2025) framework, where humans set objectives and input data (see also Simon, 1988, p. 177ff). While there is debate on whether problem finding is categorically distinct from problem solving in terms of required capabilities and as antecedents of innovation and value creation,[6] this paper's theoretical focus is on problem solving and its associated outcomes. The phases and sequencing of problem finding are outside the paper's scope (see Nickerson et al., 2012 for a discussion), and in line with Raisch and Fomina (2025), the formulation and prioritization of objectives are treated as exogenous. The problem-solving phase is conceptualized as a joint search process involving hybrid agency (Murray et al., 2021; Raisch & Fomina, 2025), characterized by problemistic search (Cyert & March, 1963; Gavetti, Greve, Levinthal, & Ocasio, 2012). We distinguish two sequential stages of problem solving: *problem definition* and *solution search* (Posen et al., 2018).

The *problem definition* stage begins with generating diverse cognitive representations of the search space, referring to mental models used to generate predictions about the real world, which guide the exploration needed to identify potential solutions (Csaszar & Levinthal, 2016, pp. 2031–2032).[7] In this stage, humans identify and clarify problem elements through scope reduction and modularization into manageable subproblems (Baumann, Schmidt, & Stieglitz, 2019). In the *solution search* stage, humans generate candidate solutions in the search space, frequently through recombining existing knowledge (Fleming, 2001; Nelson & Winter, 1982), then focusing on evaluating and selecting the most promising solutions (Posen et al., 2018).

Search generally tends toward local and incremental exploitation, relying on existing knowledge, even though superior solutions often require distant, exploratory search (March, 1991). This is particularly pertinent for innovation, which demands more resources and greater recombination of knowledge, including developing appropriate cognitive representations to evaluate and select cognitively distant and innovative solutions (Gavetti et al., 2012). The search process is iterative and characterized by experiential or vicarious learning from performance feedback. It concludes when a satisficing solution – one that is satisfactory rather than optimal, due to bounded agent rationality – is identified (Cyert & March, 1963; Posen et al., 2018). The quality of identified solutions and realized outcomes is ultimately a function of an agent's available resources, capabilities, and knowledge base, which shape their ability to pursue both divergent and convergent search paths effectively (Katila & Ahuja, 2002; Posen et al., 2018).

Applying this analytical lens and drawing on theory relating to *convergent* versus *divergent* thinking (Guilford, 1956),[8] tasks associated with cognitive representation in the problem definition stage and solution generation in the solution search stage are conceptualized as largely *divergent*. Conversely, the tasks that agents carry out relating to problem clarification and scope reduction in the problem definition stage, as well as the evaluation, selection, and post-search in the solution search stage, are seen as largely *convergent*. This distinction aligns with prior research that conceptualizes problem solving as an iterative search process, where exploration involves generating and representing potential solutions in the search space, while exploitation involves evaluating and

[6] This debate concerns whether problem finding and problem solving are fundamentally distinct processes (Verganti et al., 2020). For instance, Simon (1988) subsumed problem finding under problem solving, whereas Csikszentmihalyi (1988a, 1988b) argued that they involve categorically different strategies. More recently, von Hippel and von Krogh (2016) suggested that problem solving may proceed either through problem finding followed by search, or through the serendipitous discovery of "need-solution pairs" without requiring problem formulation. Felin and Zenger (2016) critiqued this view, instead arguing for the importance of guided problem finding and solving. For a synthesis, see Andriani, Ali, and Mastrogiorgio (2017).

[7] These cognitive representations may take the form of lower-dimensional maps of the solution space or a representation of the problem structure, bounding the range of solutions that are contemplated (Csaszar & Levinthal, 2016).

[8] *Convergent* thinking is a conventional and logical process using existing knowledge to arrive at a correct or optimal solution. In contrast, *divergent* thinking is a flexible, associative, and transformative process involving generating multiple original options through novel combinations of existing knowledge. Both are required and complementary in effective problem solving, whereby divergent thinking enables creative generation of possibilities, while convergent thinking facilitates evaluation and selection (Cropley, 2006; Guilford, 1956; Jaarsveld & Lachmann, 2017).

narrowing down these alternatives to identify a satisficing solution (Cyert & March, 1963; March, 1991). Prior research has applied this innovation search perspective through the divergent-convergent framework to conceptualize and examine AI's role in problem solving (Bouschery, Blazevic, & Piller, 2023; Hermann & Puntoni, 2024; Marion, Moghaddam, Ciuccarelli, & Wang, 2023).

Following the problem-solving stage, the search outcome can be assessed in terms of performance and organizational adaptation (Baumann et al., 2019; Posen et al., 2018), where superior (more innovative) outcomes are typically associated with greater search *depth* (the extent of reusing existing knowledge) and search *scope* (the degree of generating and applying new knowledge) (Katila & Ahuja, 2002; Raisch & Fomina, 2025). Though not the only conceptualization of innovation, this search-based perspective provides a robust analytical lens for understanding how organizations combine human and artificial intelligence in problem solving.

3. Main implications of GenAI on organizations and management

GenAI can offer distributed and ubiquitous capabilities in information processing and reasoning to enable enhanced and distributed problem solving (Boussioux et al., 2024; Feuerriegel, Hartmann, Janiesch, & Zschech, 2024). While emerging discussions of GenAI's potential societal and organizational implications draw comparisons to the rapid and transformative adoption of electrification, personal computers, and predictive AI (Acemoglu, Autor, & Johnson, 2023; Agrawal, Gans, & Goldfarb, 2023a; Bick et al., 2024), there is limited research exploring AI's creative dimension and its implications for organizations (Amabile, 2020; see Jia, Luo, Fang, & Liao, 2024 for an exception). Building on the preceding section's innovation search framework, this paper explores how GenAI's emergence impacts organizations and management along four key and progressively building dimensions: *i) its nature as a GPT*, which enables it to function as *ii) a catalyst for exploratory innovation,* allowing it to serve as *iii) a complementary cognitive artifact*, ultimately acting as *iv) a democratizing force in value creation* that compounds and amplifies the expected impact of the preceding dimensions.

(i) *GenAI as a GPT.*

GenAI is emerging as a transformative GPT – a highly impactful innovation like the steam engine, electricity, and computers that is pervasive, continually improving, and innovation spawning (Bresnahan & Trajtenberg, 1995), marking a significant leap beyond predictive AI's capabilities. While predictive AI can drive innovation across industries (Brynjolfsson, Rock, & Syverson, 2017; Goldfarb, Taska, & Teodoridis, 2023; Trajtenberg, 2019), GenAI offers broader applicability with more generalizable reasoning and learning capabilities (Bick et al., 2024). Unlike the comparatively task-specific nature of predictive AI, which is typically trained and used for optimization or classification tasks in the convergent stages of problem solving, GenAI exhibits adaptability across a wide range of domains (Berg et al., 2023; Bommasani et al., 2022). This suggests that GenAI potentially surpasses predictive AI by enabling novel transversal applications, effectively constituting a GPT (Eloundou, Manning, Mishkin, & Rock, 2024). For example, frontier models like GPT-4 can generate coherent text, code, and images, illustrating their adaptability across different industries and functions (Berg et al., 2023; Epstein et al., 2023).

In the innovation search framework depicted in Fig. 1, predictive AI has primarily augmented convergent tasks in the solution search stage, assisting in evaluating and selecting solutions through optimization and classification capabilities. GenAI represents a significant advancement by extending AI's role across the problem definition and solution search stages (Raisch & Fomina, 2025). For example, LLMs can both analyze and generate coherent and useful language, surpassing predictive AI's more limited text processing and classification capabilities in natural-language processing (NLP) applications (Bommasani et al., 2022).

In the problem definition stage, GenAI's generative capabilities enable richer cognitive representations by processing unstructured and multimodal data, facilitating the retrieval and recombination of organizational knowledge. This enhances the divergent tasks of identifying and framing problems. In the solution search stage, GenAI enhances divergent as well as convergent tasks by generating a wider range of potential solutions and improving the evaluation process through advanced reasoning and knowledge integration. Unlike predictive AI, which is limited to processing existing data for classification or optimization, GenAI's ability to generate novel outputs allows it to create solutions beyond existing knowledge across the problem-solving stages (Bouschery et al., 2023; Raisch & Fomina, 2025).

Illustration of divergent* versus *convergent use of GenAI.

The following illustrates and contrasts GenAI's convergent and divergent use, along with the importance of distinguishing between the application paradigms. Recent research has highlighted how even frontier LLMs have struggled with seemingly simple arithmetic tasks (e.g., "20 + 183") due to their non-deterministic nature, leading them to be framed as inadequate or unreliable (Zhou et al., 2024, p. 61). This limitation can be overcome by invoking a convergent logic through prompts like "use Python," which directs models like ChatGPT or Claude to perform calculations programmatically using languages like Python or JavaScript in a deterministic code environment before translating results back to natural language.

This principle extends to other tasks like counting word or letter frequencies, as shown in Fig. 2, illustrating convergent use where ChatGPT is unable to count occurrences of the letter "r" in the word "strawberry" using its default mechanism for generating output (Eaton, 2024), but becomes accurate when directed to use programmatic counting. Conversely, Fig. 3 demonstrates the deliberate use of the same model with the same elements ("strawberry" and "r") with a goal associated with divergent thinking, namely creative writing. In the example, ChatGPT is also prompted to produce the initial, divergent prompt itself, which is then used to produce the creative writing output.

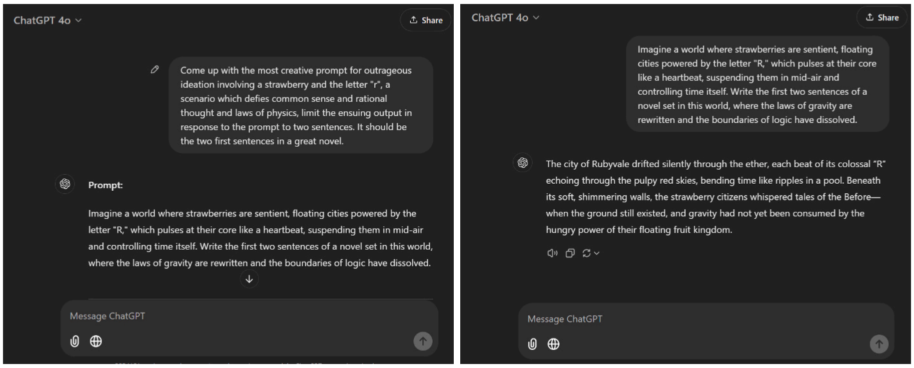

Fig. 2. Illustration of convergent use of an LLM (ChatGPT 4o, November 3, 2024).

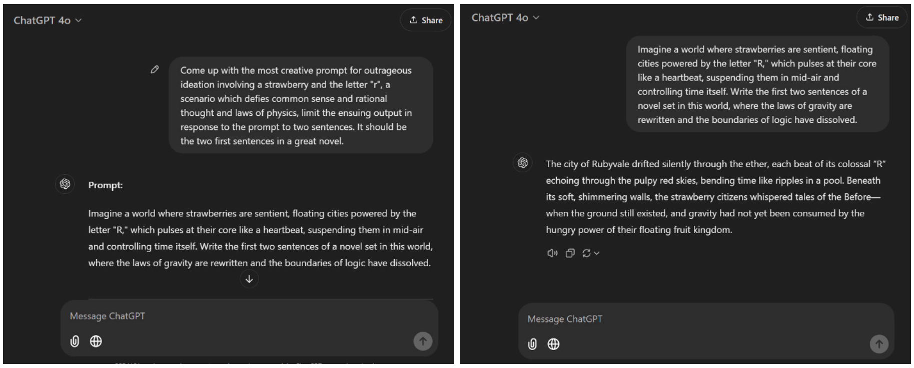

Fig. 3. Illustration of divergent use of an LLM (ChatGPT 4o, November 3, 2024).

Realizing GenAI's full potential will likely depend on the development of complementary assets (Brynjolfsson, Rock, & Syverson, 2021; Goldfarb et al., 2023).[9] Such assets include human and organizational resources – particularly domain expertise, judgment, and intuition (Agrawal, Gans, & Goldfarb, 2018; Choudhury, Starr, & Agarwal, 2020) – as illustrated by the decisive role of new AI-related skills when chess players integrated AI into tournaments (Krakowski et al., 2023). Such new skills may include the ability to use GenAI appropriately in both convergent and divergent tasks, with an understanding of GenAI's emerging capabilities as well as its technological constraints across problem-solving stages. This extends to the development of valid measures to evaluate and track model behavior and performance across both intrinsic properties and task-specific applications, including the understanding and documentation of emergent capabilities (Bommasani et al., 2022). New competencies will also likely be required to remain competitive and to assume higher-order tasks relating to AI adoption and implementation (Krakowski et al., 2023; Verganti et al., 2020).

AI is expected to bring significant economic and organizational changes and challenges, similar to historical technological revolutions. In divergent tasks, GenAI's limitations include a lack of long-term memory, limited hierarchical planning, and restrictions in continual learning and context-dependent adjustment, which can significantly impact the quality of cognitive representations. In convergent tasks, GenAI's susceptibility to produce "hallucinations", referring to factually inaccurate output with a "tendency to appear as reasonable or aligned with truthful inferences," can lead to costly mistakes and deteriorating trust in the generated solutions (Bubeck et al., 2023, p. 82) unless humans remain engaged and critically reflect on the output (Hannigan, McCarthy, & Spicer, 2024).

Widespread adoption is associated with increasing energy consumption in training and operating GenAI models, raising environmental sustainability concerns and suggesting a need for expanded availability of renewable energy sources. The models' significant training and operating costs effectively pose barriers to entry for participation in their development. The high energy consumption and financial costs indicate a need for more efficient model architectures (Bender et al., 2021; Weidinger et al., 2022).

GenAI models have been shown to exhibit biases stemming from their training data, which often reflects historical inaccuracies, inequalities, and a limited reality. This creates risks that their widespread deployment may introduce, perpetuate, or entrench biases, particularly when there is inadequate documentation and evaluation of model development, testing, and performance across different populations and contexts (Bender et al., 2021; Bommasani et al., 2022).

[9] For example, electricity required factories and processes to be redesigned, taking up to three decades for productivity effects to materialize; similarly, AI is expected to require substantial societal and labor adjustments (David, 1990).

Research as well as practice therefore generally remain limited in an optimization paradigm (Cabantous & Gond, 2011) where AI is seen as an exclusively convergent technology that is expected to provide accurate answers or solutions (Hannigan et al., 2024; Lindebaum & Fleming, 2024), rather than distinguishing between convergent and divergent applications of the technology. GenAI's generative and aleatory nature can be seen as a useful *feature* (creativity) promoting divergent thinking rather than a *bug* (hallucination), depending on the task and context. Accordingly, the complementary human and organizational assets needed to enable value creation with GenAI for creativity and innovation are even more uncertain compared to predictive AI (Berg et al., 2023).

Given the pace of technological development and the significant impact GenAI is already having on the economy and work (Bick et al., 2024), organizations and society will need to adapt and transition rapidly to leverage these technologies effectively. This includes developing new strategies to balance automation through GenAI with the need to maintain human expertise and creativity and overcoming inherent inertia through augmentation, to integrate and utilize GenAI effectively (Hanelt, Bohnsack, Marz, & Antunes Marante, 2021; Raisch & Krakowski, 2021).

i) *GenAI as a GPT: EQT Motherbrain*

The private equity company EQT's *Motherbrain* platform exemplifies the evolution from predictive to generative AI as a GPT. Initially, EQT Motherbrain used predictive AI for pattern matching in the convergent stage of solution search, evaluating potential acquisitions through a "corporate dating app." The platform evolved to incorporate bespoke GenAI models that span divergent as well as convergent stages of problem solving. In divergent application, the system enables exploration in M&A sourcing through natural language queries like "Which companies may use computer vision in the healthcare industry?" This enables the generation of novel investment hypotheses and combinations that were not immediately apparent. A convergent use involves GenAI enhancing evaluation through sector classification and target screening, enabling thematic investment analysis. This shift required new complementary assets, particularly the development of Motherbrain Labs, where technologists and investment professionals collaborate to leverage the technology effectively across the problem-solving process.

~ Interview with Alexandra Lutz, Head of Motherbrain at EQT, November 2024

(ii) *GenAI as a catalyst for exploratory and combinatorial innovation.*

Building on GenAI's general-purpose nature, its generative capabilities enable a significant shift from exploitative to exploratory applications, allowing the development of qualitatively new ideas and solutions (Kulkarni et al., 2024; Raisch & Fomina, 2025).[10] Through "generativity," defined as "a sociotechnical system where social and technical elements interact to facilitate combinatorial innovation" (Thomas & Tee, 2022, p. 255; Yoo, Boland Jr., Lyytinen, & Majchrzak, 2012), GenAI facilitates the large-scale recombination of ideas and concepts, potentially driving combinatorial innovation.

By leveraging vast volumes of training data and processing new and multimodal data, GenAI can act as a catalyst for innovation by identifying potential combinations of existing ideas or technologies that might not be immediately apparent to human decision makers. This generativity is enabled by GenAI's quasi-random sampling mechanism, which enables "aleatory creativity" under constraints (Rietzschel & Rus, 2022). The probability distribution of the next iterative output then acts as a creative constraint, such as sequentially sampled tokens in the case of LLMs. Consequently, GenAI can expand the scope of exploratory search through combinatorial and serendipitous innovation (Busch, 2024; Mariani & Dwivedi, 2024; Robertson, Ferreira, Botha, & Oosthuizen, 2024).

Applying the innovation search framework, GenAI can augment the divergent tasks, particularly in the problem definition and solution generation stages, by greatly increasing idea generation and knowledge recombination. Viewed as a funnel, performance in an innovation process is contingent on generating many initial ideas, given that only a small percentage will ultimately be successful (Sutton, 2010), whereby GenAI can be seen as providing vastly more solutions for human agents to consider in the start of the funnel. GenAI thus effectively broadens the search space, enhancing the likelihood of viable innovations (Bouschery et al., 2023). This capability accelerates creative processes across domains such as art and literature (Epstein et al., 2023), organizational strategy (Doshi, Bell, Mirzayev, & Vanneste, 2024), and scientific research (Korinek, 2023).

In the problem definition stage, GenAI processes unstructured and multimodal data, creating novel, synthetic data that enriches cognitive representations by drawing on abilities relating to emotion, reasoning, and creativity (Epstein et al., 2023). In the solution search stage, it enables diverse and novel solutions through its generative mechanisms, along with more comprehensive approaches and perspectives for evaluation. In the pharmaceutical industry, GenAI accelerates drug discovery by generating and evaluating molecular structures at a scale that vastly outpaces predictive AI applications (Swanson et al., 2024). Thus, GenAI can qualitatively reshape innovation, enabling faster innovation cycles and reduced time-to-market.

Realizing its innovative potential will likely require fundamental changes in organizational structures and processes to enable distributed innovation in convergent as well as divergent tasks. While traditional organizational structures emphasized centralized control and standardized processes, GenAI's generative capabilities enable more fluid and adaptable organizational forms. Its ability to

[10] While AI has been used in idea generation (Raisch & Krakowski, 2021), such as generative adversarial networks (GANs) in product design and medical applications (Aggarwal, Mittal, & Battineni, 2021; Marion et al., 2023), this paper argues that GenAI radically extends AI's GPT-like nature to a much broader range of tasks, enabling more exploratory capabilities and learning opportunities than previous iterations.

process and generate insights from unstructured data enables more distributed innovation processes, potentially reducing reliance on centralized expertise while creating new coordination challenges compared to current conceptualizations (Kyriakou, Nickerson, & Sabnis, 2017).

Novel configurations of human-AI co-creativity reshape traditional hierarchies in how organizations structure creative tasks and innovation processes (Fang He, Shrestha, Puranam, & Miron-Spektor, 2023; Mariani & Dwivedi, 2024). This suggests that using GenAI successfully to catalyze innovation may depend on balancing local autonomy with strategic alignment (Ellinger, Gregory, Mini, Widjaja, & Henfridsson, 2024; Joseph & Sengul, 2024), particularly in matching human and GenAI capabilities to specific task requirements across organizational contexts. This balance becomes critical given evidence that while average creativity generally increases through human-AI collaboration in divergent tasks (Boussioux et al., 2024; Doshi & Hauser, 2024), solution diversity may decrease due to either human or AI inclusion in the creative search process, where the highest performers may experience limited or even negative effects (Dell'Acqua et al., 2023; Zhou & Lee, 2024).

Several limitations are worth considering when it comes to GenAI's effectiveness as a catalyst for innovation. As with applications based on ML, GenAI's capabilities are constrained by partial and systematically limited training data that can lead to biased or culturally and linguistically limited exploration and innovation outcomes (Bommasani et al., 2022; Ray, 2023), along with difficulties in deriving and validating the outputs from GenAI models (Weidinger et al., 2022). Concerns have also been raised that creative economies may be undermined through crowding out human creativity with incremental GenAI-driven innovation, along with legal and ethical challenges relating to ownership and attribution of innovations as well as harms caused through using GenAI (Bommasani et al., 2022; Weidinger et al., 2022).

GenAI builds on DL in the initial prediction stage, meaning that it fundamentally operates through interpolations in model representations of its training data, rather than extrapolative generalizations beyond the data.[11] While this means that GenAI models cannot truly explore options outside their training distribution during divergent search stages (Chollet, 2021, p. 129f), the limitation creates opportunities for human-AI complementarity. GenAI's vast training data – orders of magnitude larger than individual human experience – enables exposure to novel knowledge, perspectives, and combinations thereof (Hubert et al., 2024) that would be otherwise inaccessible to humans with comparatively much more limited and idiosyncratic experience and representations. Hereby, GenAI's generativity and aleatory sampling mechanism (which constitutes productive randomness) acts as a catalyst of serendipitous innovation (Busch, 2024), while enabling preserved human agency in creative direction through extrapolation and imagination (Fang He et al., 2023).

ii) *GenAI as a catalyst for exploratory and combinatorial innovation: Spotify DJ*

An illustrative example of GenAI acting as a catalyst for exploratory and combinatorial innovation is Spotify's development of its *DJ* feature that personalizes the user listening experience at scale. Faced with the overwhelming choice in audio content, Spotify sought to simplify and enrich the listening journey by combining personalized music selections with insightful commentary.

Importantly, Spotify's music and culture specialists, data curators, and scriptwriters worked alongside GenAI to create unique, tailored listening sessions for each user. Divergent tasks involved Spotify leveraging GenAI to process vast amounts of user data and music information to identify potential combinations of songs and contextual narratives that were not immediately apparent to human curators, which broadened the innovation search space. Convergent uses of GenAI further enable voice commentary insights about tracks, artists, and genres in different languages at a scale that would not otherwise be possible.

~ Interview with Emily Galloway, Personalization Design Lead at Spotify, June 2024

(iii) *GenAI as a complementary cognitive artifact.*

Building on Krakauer's (2016) distinction between competitive and complementary cognitive artifacts, GenAI represents a qualitative shift in how technology, particularly AI, can affect and potentially enhance human cognition. This specifically points to augmenting human learning, cognitive representations, and creativity through its generative capabilities. *Competitive* cognitive artifacts are tools such that "when we are deprived of their use, we are no better than when we started" (e.g., a calculator that provides temporary arithmetic augmentation and yields dependency rather than lasting cognitive benefits), while complementary cognitive artifacts enable learning through sustained skill improvements that persist even when the artifact is no longer available, since "after repeated practice and training, the artifact itself could be set aside and its mental simulacrum deployed in its place" (e.g., an abacus, whose user develops arithmetic capabilities that eventually render the tool redundant) (Krakauer, 2016).

Applied to AI, this conceptualization distinguishes between AI that merely augments performance without promoting learning

[11] Different AI architectures may enable varying degrees of exploration. For instance, genetic algorithms with evolutionary mechanisms and random mutations might enable extrapolation beyond training data, potentially enhancing human creative exploration (Dietrich & Haider, 2015; Miikkulainen & Forrest, 2021). Other suggested approaches and extensions include reinforcement learning (Cao, Sheng, McAuley, & Yao, 2023) and neuro-symbolic AI (Colelough & Regli, 2025). Open questions remain regarding the methods different AI models use to produce novel and useful outputs, such as convex combinations or extrapolation (Horzyk, 2014).

(competitive artifact) and AI that promotes enduring skill development (complementary artifact). While predictive AI tends to function as a competitive artifact by optimizing tasks without engaging humans in metacognition or learning, GenAI's interactive and generative nature enables it to be a more impactful complementary artifact. This stems from two key mechanisms: first, GenAI's vast training data, which exceeds the distribution of individual human experience by orders of magnitude, enables exposure to novel knowledge and combinations thereof; second, its natural language interface and generative responses enable learning through dialogue and exploration that can persist beyond its immediate use.

In the innovation search framework, GenAI can function as a complementary cognitive artifact that enhances both divergent and convergent tasks through distinct mechanisms. In the problem definition stage, GenAI assists humans to develop richer cognitive representations by deconstructing complex problems into manageable subcomponents and eliciting novel perspectives. This enables better exploration of solution possibilities and promotes interaction and learning dynamics (Jiang, Shao, Ma, Semnani, & Lam, 2024). In the solution search stage, GenAI can facilitate the exploration of cognitively distant opportunities by generating new combinations of ideas and perspectives, helping individuals move beyond existing or conventional mental models and domain constraints. This is enabled through human-level capabilities exhibited by contemporary frontier models involving emotional intelligence (Wang, Li, Yin, Wu, & Liu, 2023) and abilities related to theory of mind (Kosinski, 2024; Strachan et al., 2024).

For instance, models like Pi (Inflection AI) explicitly build on LLM abilities to emulate human conversation and empathy, experiencing widespread adoption as conversational partners (Siddals, Torous, & Coxon, 2024). A remarkable development is the use of GenAI to create "interactive simulacra" (Park et al., 2023), an instance of "silicon sampling" (Argyle et al., 2023), where GenAI creates virtual agents replicating human behavior and cognitive patterns with high fidelity across contexts (Cui, Li, & Zhou, 2024). This enables humans to develop a persistent mental simulacrum (Krakauer, 2016) through simulation and roleplay, enhancing capabilities in social and organizational contexts involving interpersonal information flow and collaboration. In convergent tasks, GenAI supports clarification and evaluation by providing iterative insights and feedback that help refine solutions and enable richer performance feedback. In the healthcare context, medical professionals engaging with GenAI for diagnostic reasoning have shown sustained analytical improvements (Stade et al., 2024).

GenAI's effectiveness as a complementary cognitive artifact will depend on active human engagement and reflection. Its black-box nature and the inherent opacity of DL, along with ongoing modifications by system designers, can discourage deeper human learning if used passively (van den Broek, Sergeeva, & Huysman, 2021). Further concerns arise from human-computer interaction harms and loss of human autonomy and agency, such as anthropomorphization leading to misplaced trust and excessive dependency (Ray, 2023; Weidinger et al., 2022). Intentional design of human-AI interaction patterns can however promote complementary learning effects that reconfigure expertise and workflows (Barrett, Oborn, Orlikowski, & Yates, 2012), rather than GenAI becoming a competitive artifact characterized by overreliance and skill degradation (Chen & Chan, 2024; Lindebaum & Fleming, 2024).

Overreliance on GenAI could lead to a decline in essential skill development, particularly among junior professionals who may not receive adequate experiential learning opportunities (Beane & Anthony, 2024; Brynjolfsson, Li, & Raymond, 2023). Recent research has however found a performance compression effect where inexperienced or lower-performing workers appear to benefit more from GenAI assistance compared to senior or high-performing individuals (Boussioux et al., 2024; Brynjolfsson et al., 2023), though GenAI might negatively impact the development of new expertise and tacit knowledge critical for innovation. Further, the effectiveness of hybrid agency may be hard to measure (Weidinger et al., 2022), and is likely to depend on matching human-AI interactions to expertise levels, attitudes, and task characteristics, including temporal dynamics (Burton, Stein, & Jensen, 2020; Raisch & Fomina, 2025).

Realizing GenAI's potential to enhance human capabilities may also require maintaining human involvement in problem-solving processes even when the human or hybrid agents do not possess superior task-related capabilities (e.g., Goh et al., 2024). This may necessitate a "human in the loop" approach that prioritizes metacognition and learning over pure efficiency or performance objectives (Glikson & Woolley, 2020). Unlike predictive AI, GenAI's natural-language capabilities and interactive nature make such learning-focused implementation feasible at scale, enabling it to function as a complementary cognitive artifact across organizational contexts. This suggests a need for educational and training programs to rapidly adapt to the uncertainties introduced by GenAI (Oravec, 2023; Rudolph, Tan, & Tan, 2023), ensuring that human learners retain the expertise necessary to collaborate meaningfully with AI systems.

iii) *GenAI as a complementary cognitive artifact: Entrepreneurship education*

An example of GenAI serving as a complementary cognitive artifact can be found in an accelerator-style entrepreneurship course the author has given since 2022. The course emphasizes frameworks and concepts related to design thinking and the lean startup methodology (Mansoori & Lackéus, 2020; Neck & Corbett, 2018).[121] Students are trained and encouraged to use GenAI tools throughout their startup projects, from early stages of empathy and ideation to final stages of validating product-market fit and preparing pitches for *Shark Tank*-style sessions with expert judges from the venture capital industry. Students have used GenAI to generate user personas, brainstorm features, create low-fidelity prototypes, simulate user interactions, conduct pre-mortems, and practice pitching through LLM roleplay, among other emergent applications.

"We used an AI tool (ChatGPT) as the respondent for the surveys. ChatGPT ran these hypothetical surveys 100 times and collected data about the (hypothetical) answers it provided as a simulated retired/young professional."

~ Student working on startup relating to onboarding employees and organizational knowledge transfer

"I have since begun using ChatGPT, commanding it to emulate an 'average Gen-Z consumer' alongside a description of the app. I asked several questions: What is your opinion of the app idea? Would the app solve a problem you have? What features would you like to see on the app? Would you pay for the service the app is providing?"

~ Student working on startup relating to finding the sales point for fashion seen in media

By engaging with GenAI in these tasks, students enhanced their cognitive representations and learning processes throughout the startup process. For instance, they used GenAI for divergent thinking to simulate surveys and gather hypothetical customer insights, allowing them to refine their business models based on diverse perspectives, while GenAI enabled convergent use in risk prioritization and competitor mapping and analysis. This active and reflective engagement with GenAI enabled a documented deeper understanding and skill development that persisted beyond the classroom, including prompting it for clarifications relating to priorities in the course.

"We used ChatGPT to determine the perceived value and the purchase intention of potential customers by creating a survey on a four-point scale. ChatGPT helped us create the survey, but we also used the AI tool to answer the survey."

~ Student working on startup relating to connecting drivers with free parking slots

"Fun fact relating to prioritizing content was that we initially found it hard to interpret the assignment, whether to please investors or faculty. Hence, we asked ChatGPT to interpret it for us."

~ Student working on startup relating to optimizing the deployment of electric vehicle charging infrastructure (Author's entrepreneurship course, 2023 cohort)

(iv) *GenAI as a democratizing force in AI adoption and innovation.*

GenAI's accessible, conversational user interfaces and broad applicability across tasks and domains can democratize AI adoption, enabling a wider range of individuals and organizations to harness its potential for value creation and innovation. This availability and engagement of more human agents at scale can in turn be expected to amplify and compound the suggested impact and ramifications associated in the preceding dimensions.

Unlike predictive AI, which often requires technical expertise and infrastructure to implement and use effectively, GenAI's pre-trained nature and natural-language interfaces lower adoption barriers. This allows humans without IT, data science, or programming skills to engage with AI systems, even sparking debates about whether prompting could replace programming (Sætra, 2023; Welsh, 2022). The accessibility and affordability of contemporary frontier models, such as GPT-4o for general-purpose multimodal uses, GitHub Copilot for coding and software development, or Pi for tasks involving social and emotional dimensions, along with open models like Llama 3 (Meta) and DeepSeek-R1 (DeepSeek AI), have made advanced AI capabilities widely available at little to no cost. Increasingly efficient architectures and affordable cloud computing capacity enable local deployment as well as fine-tuning of models for customized applications (Zhang, Cao, Shen, & Cui, 2024). This democratization implies that innovation through generativity, recombination, and enhanced learning and cognition can be scaled up throughout organizations and society.

Once more applying the innovation search framework, GenAI can enhance divergent as well as convergent tasks by making both predictive AI and GenAI capabilities accessible to a broader range of human beings. In the problem definition stage, its natural-language capabilities enable humans to participate in ideation and framing with few technical barriers, promoting decentralized and democratized innovation processes (Eapen, Finkenstadt, Folk, & Venkataswamy, 2023). In divergent applications, non-technical individuals can generate creative solutions and recombine knowledge across domains, expanding the search space and increasing the likelihood of viable innovations. In healthcare, GenAI models have served as "universal translators" for information management in complex medical tasks (Kather, Ferber, Wiest, Gilbert, & Truhn, 2024, p. 2708). In convergent tasks including evaluation and selection, GenAI can assist humans by providing accessible insights and feedback, leveraging existing knowledge more effectively across an organization (McKendrick, 2024). Returning to the healthcare context, GenAI applications like AI chatbots provide empathic and personalized patient interactions, contributing to more human-centric care and making qualified healthcare services more accessible (Ayers et al., 2023). This enhanced participation across stages amplifies the complementary cognitive benefits by engaging a wider range of cognitive perspectives and capabilities.

This broad applicability can empower individuals and smaller organizations to compete with larger entities by accessing state-of-the-art AI tools at low or no cost, potentially leveling the playing field in innovation and strategic planning (Feuerriegel et al., 2024). In the content creation industry, for instance, small-scale platforms use GenAI to offer personalized content at lower costs (Wessel, Adam, Benlian, & Thies, 2023). The aforementioned performance compression effect (Boussioux et al., 2024; Brynjolfsson et al., 2023) also suggests that GenAI can help reduce skill gaps and equalize access to training and learning at an even larger scale than predictive AI (cf. Gaessler & Piezunka, 2023).

Such democratization and equalizing effects may extend beyond organizational boundaries to address societal inclusion. This effect extends to marginalized communities, serving as a form of digital inclusion by design through GenAI's highly emergent affordances

[12] This experimental curriculum approach was preregistered and received ethical approval from the author's institution. Student quotes are by individuals who provided informed consent for research purposes, shared with the author only after course completion and assessment.

and generativity (Faik, Sengupta, & Deng, 2024). Potential and emerging applications range from mental health, such as preventing suicidal ideation in 3 % of participants (Maples, Cerit, Vishwanath, & Pea, 2024) to neurodevelopmental disorders and supporting diagnosis and treatment of dyslexia, autism, and ADHD (Cao, Martin, & Li, 2023; Tang et al., 2024; Zhao et al., 2024). GenAI has even been applied to cross-species communication through the *Earth Species Project*, interpreting animal sounds and communication (Hagiwara, 2023).

GenAI's democratizing potential also presents several challenges and risks. One concern is the widespread adoption of similar models, trained on primarily English internet data, suggesting that models may exhibit a skewed representation of reality that amplifies bias (Bender et al., 2021). Adoption could lead to homogenization, potentially limiting diversity in thought and creative direction among humans who rely on the technology for exploration and learning (Bommasani et al., 2022). The black-box nature of GenAI models can also impede understanding and transparency, raising questions about the extent to which humans can critically assess and interpret GenAI-generated outputs (Raisch & Fomina, 2025; van den Broek et al., 2021).

Large-scale GenAI adoption could enable mass data collection and surveillance, censorship, as well as fraud or manipulation if misapplied. Privacy is a related concern, as models may disseminate or leak private or sensitive data (Weidinger et al., 2022). Another significant challenge is the potential for GenAI to exacerbate issues like polarization, misinformation, and filter bubbles. Though evidence is mixed (cf. Asimovic, Nagler, Bonneau, & Tucker, 2021; Bail et al., 2020; Budak, Nyhan, Rothschild, Thorson, & Watts, 2024), predictive AI has been associated with reinforcing biases and spreading misinformation (Spohr, 2017). GenAI's ability to generate content could amplify these issues if misused by ignorant or malicious actors (Weidinger et al., 2022). Used as a complementary artifact, GenAI may however enable a wider part of society to critically analyze and counteract misinformation (Costello, Pennycook, & Rand, 2025).

Finally, access to GenAI technology is not uniformly distributed globally and is influenced by decisions made by companies offering commercial models, as well as government policies that enable or constrain access and use (Sathish, Lin, Kamath, & Nyayachavadi, 2024). Together with disruptions to labor markets where some forms of work are displaced, this may cause socioeconomic disparities through uneven access to benefits due to hardware, software, and skill constraints (Bommasani et al., 2022; Weidinger et al., 2022),

(iv) GenAI as a democratizing force in AI adoption and innovation: KBLab

An example of GenAI's democratizing potential is *KBLab*, the data lab of the National Library of Sweden (*Kungliga biblioteket*). KBLab has used the library's extensive collection, spanning ten centuries and comprising 26 petabytes of data, to develop open-access LLMs for Swedish. This initiative aims to make advanced AI tools available to a broad audience, including academia, public sector agencies, and private businesses. KBLab recognized that the National Library's vast archival resources presented a unique opportunity to contribute to AI research and innovation. A centuries-old law requiring a copy of every publication in Swedish to be submitted to the library resulted in a comprehensive collection across various media, from books and newspapers to digital content. KBLab plans to develop open-access multimodal language models for Swedish and other Scandinavian languages, aiming to train models on at least one terabyte of text – addressing concerns about homogenization by expanding linguistic diversity in AI models and making them accessible to non-English-speaking communities. KBLab also acknowledges the potential risks associated with GenAI misuse, particularly concerning digital misinformation and propaganda, emphasizing the importance of responsible development and aiming to ensure that AI advancement supports research, innovation, and truth.

~ Interview with Love Börjeson, Head of KBLab at the National Library of Sweden, November 2024

suggesting that democratization and (equitable) distribution of benefits is not an automatic outcome (Papadopoulos & Cleveland, 2023).

Together, these four dimensions illustrate how GenAI extends and redefines AI's role in management and organizations, with Table 1 providing an overview of key takeaways. By acting as a GPT, catalyzing exploratory innovation, serving as a complementary cognitive artifact, and democratizing AI adoption, GenAI challenges AI's dominant convergent-oriented narrative. As organizations increasingly integrate GenAI, new frameworks and strategies that account for its unique characteristics will likely be needed.

4. Implications for practice and policy

Seeing AI as an evolving frontier of machine capabilities (Berente et al., 2021), GenAI represents a significant expansion in the tasks AI can perform, fundamentally altering the allocation of work between humans and machines. Extending the search- and agency-based perspective in this paper to derive four critical dimensions of GenAI's expected impact, a task-based perspective (Acemoglu, Autor, Hazell, & Restrepo, 2022) is particularly suitable for analyzing the associated implications for policy and practice. This perspective

Table 1
Key insights.

Dimension	Task application	Key insights
i) GenAI as a GPT	Divergent	Extends AI capabilities through richer problem representations and broader exploration via multimodal data processing. Realizing these benefits demands active human engagement to overcome memory limitations while monitoring biases.
	Convergent	Improves solution evaluation and selection through advanced reasoning and knowledge integration beyond predictive AI capabilities. Effectiveness will depend on human oversight for detecting hallucinations and critical reflection, supported by AI-related skills.
ii) GenAI as a catalyst for exploratory and combinatorial innovation	Divergent	Enables large-scale idea generation and recombination, vastly expanding creative exploration beyond predictive AI. Biased or partial training data may however limit genuine novelty and contested ownership issues require suitable governance.
	Convergent	Accelerates innovation cycles through rapid iteration and evaluation of novel solutions, while potentially decreasing solution diversity in human-AI collaboration. Effectiveness depends on organizational restructuring and balance with validation of outputs.
iii) GenAI as a complementary cognitive artifact	Divergent	Enhances cognitive representations through interactive engagement, but risks creating overreliance and misplaced trust. This implies a need for intentional design of human-AI interaction patterns that prioritize metacognition and preserve human primary agency.
	Convergent	Enables sustained analytical skill development through iterative feedback but may impede the development of expertise without adequate experiential learning. Effectiveness depends on maintaining active human involvement and appropriate interaction design.
iv) GenAI as a democratizing force in AI adoption and value creation	Divergent	Enables broader participation in innovation through accessible interfaces, but risks amplifying biases and homogenization. Resolving these risks depends on addressing privacy concerns, preventing misuse, and ensuring equitable access.
	Convergent	Broadens participation in solution evaluation and refinement but may exacerbate socioeconomic disparities and labor market disruptions. Effectiveness depends on mitigating risks of misinformation and polarization.

enables systematic examination of how technologies like AI affect different types of tasks and their interdependencies (Acemoglu et al., 2022; Fonseca, Lima, & Pereira, 2018), given that GenAI's impact and associated implications for task allocation among human and AI agents appear heterogeneous across industries (Eisfeldt, Schubert, & Zhang, 2023) as well as in organizations (Dell'Acqua et al., 2023).

Viewed through the lens of punctuated equilibrium, where periods of stability are disrupted by rapid change (Hanelt et al., 2021; Romanelli & Tushman, 1994), GenAI represents a transformative technological development that challenges existing organizational equilibria. The emerging dynamics between human and AI agents create tensions in balancing automation and augmentation (Agrawal, Gans, & Goldfarb, 2023b; Raisch & Krakowski, 2021). This will likely require a redefinition of roles, workflows, and approaches to human-AI agency (Murray et al., 2021; Raisch & Fomina, 2025). Adjusting to this punctuated equilibrium calls for new approaches to assess and realize GenAI's potential, while mitigating risks and unintended consequences (Brynjolfsson, 2022; Eloundou et al., 2024).

4.1. Policy considerations

From a policy perspective, understanding GenAI's impact through a task-based lens reveals distinctive opportunities and challenges for labor markets and economic growth. While capital has in recent times accounted for 70 % to 80 % of productivity increases (Mischke et al., 2024), the last decades have seen stagnant labor productivity growth despite technological advancement (Brynjolfsson et al., 2017; Solow, 1987). One suggested explanation is that the benefits of AI and technological innovations have been unevenly distributed, often captured by a small number of companies rather than being spread throughout the economy. Another is that traditional productivity statistics may not fully capture the value that new technologies like GenAI generates, as intangible benefits such as improved cognitive capabilities and creative outputs are difficult to measure in GDP statistics (Brynjolfsson, Collis, & Eggers, 2019).

GenAI as a technology is positioned to have a significant impact on the economy, with estimates suggesting that 80 % of the US workforce could see at least 10 % of their tasks affected by LLMs alone, and 19 % potentially seeing 50 % or more of their tasks impacted (Eloundou et al., 2024). Unlike previous technologies that primarily affected routine tasks or specific skill levels, GenAI's capabilities span a much wider part of skill spectrum, challenging traditional models of skill-biased technological change (Acemoglu & Restrepo, 2024; cf. Fonseca et al., 2018). This is evidenced by GenAI's emerging human-level performance in non-routine tasks involving creativity and emotion – the very capabilities previously assumed to be most out of reach for AI (Brynjolfsson & Mitchell, 2017; Tegmark, 2017, p. 53).

Historical precedents provide important context for understanding GenAI's potential impact and formulate appropriate policy responses. Transitions like mechanical phone switching and the advent of the jet engine demonstrate that automation does not invariably decrease labor demand but can indirectly increase demand and output (Feigenbaum & Gross, 2024; Raj & Seamans, 2019). Emphasizing the enabling aspects of GenAI aligns with Weitzman's (1998) concept of combinatorial growth, where new ideas emerge from recombining existing ones, which in turn become components of future innovations. For example, Gutenberg's printing press combined movable type, paper, ink, metallurgical advances, and a wine press. Given the exponential increases in GenAI capabilities (Henshall, 2023), the technology can not only increase growth but, by catalyzing innovation, enable a new, exponential growth mode (Hanson, 2000), provided appropriate policies are implemented (Baily et al., 2023). This potential is particularly significant given that technological innovation generally benefits workers most when it augments their capabilities, increases quality, and when labor has a higher factor share in production (Korinek & Stiglitz, 2020).

Realizing GenAI's potential for inclusive growth will therefore require deliberate policy interventions. These have been suggested to include policies that promote innovation and competition by avoiding compliance costs that favor large players. They should also balance the benefits of allowing publicly available data to be used for training foundation models with copyright laws that incentivize the production of the data, such as by compensating creators whose data is used (Epstein et al., 2023; Schrepel & Pentland, 2024). Policies that promote the development and adoption of human-complementary AI technologies can also help distribute GenAI's benefits more broadly across society. A key priority is addressing the "Turing Trap," where AI development and implementation focuses on mimicking rather than complementing human capabilities by facilitating worker upskilling and incentivizing investment in human capital through human-complementary approaches (Brynjolfsson, 2022).

This requires policies that guide AI development and adoption by funding and putting incentives in place such that AI is deployed alongside human expertise (Acemoglu et al., 2023; Korinek & Stiglitz, 2020). Beyond traditional redistributive policies like taxes and transfers, recent research suggests addressing inequality through "predistribution" measures such as educational and healthcare policies (Bozio, Garbinti, Goupille-Lebret, Guillot, & Piketty, 2024). Regulatory frameworks should also evolve to address novel challenges in areas like data privacy and algorithmic accountability without stifling innovation and beneficial applications. These policy choices should aim to enable economic gains and ensure their equitable distribution, ensuring that GenAI's transformative potential contributes to shared prosperity that benefits all layers of society.

4.2. Practical considerations

Organizations will need to assess how to integrate GenAI into their workflows to complement rather than replace human capabilities. Unlike previous waves of AI adoption focused on convergent logic, GenAI's broad applicability requires a more nuanced implementation approach. From a task-based perspective, organizations must analyze which tasks suit automation versus augmentation through human-AI collaboration and understand how these dynamics evolve (Raisch & Fomina, 2025; Raisch & Krakowski, 2021), suggesting that traditional conceptions attributing innovation solely to human agency will require revision. GenAI democratizes knowledge retrieval and recombination, expanding innovation participation by mitigating expertise bias through its emphasis on feasibility over novelty (Eapen et al., 2023), implying a potential for radically more distributed, autonomous, and pervasive value creation in the workforce. For example, GenAI enables tackling complex architectural challenges in software development (Nguyen-Duc et al., 2023), while it transforms ideation through rapid iteration in creative industries (Eapen et al., 2023).

Effective organizational implementation will require attention to task interdependencies and investment in complementary assets including employee training, culture, and infrastructure (Kemp, 2024). Organizations will have to develop new approaches to performance measurement and incentives that align with changing work patterns and skill development (Tamayo et al., 2023). This includes enabling workers to distinguish between convergent and divergent tasks, choosing between predictive or generative AI approaches, and managing actual and perceived relative advantages in abilities between human and AI agents (Dell'Acqua et al., 2023; SimanTov-Nachlieli, 2025). Necessary skills will likely include data management, AI literacy, and AI deployment decisions (Raisch & Krakowski, 2021; Verganti et al., 2020), leveraging GenAI as a complementary artifact for learning at scale, yet at an individual worker level. Understanding contingencies in employee expertise, personality, and AI attitudes (Chen & Chan, 2024; Park & Woo, 2022), along with contextual factors like decision context and time dynamics (Burton et al., 2020; Raisch & Fomina, 2025), will likely be decisive for successful integration.

Widespread GenAI adoption may entail several challenges for organizations. Overreliance on GenAI could lead to passivity and deskilling if employees become too dependent on AI-generated output without maintaining their own expertise and critical thinking skills. To mitigate this, approaches to managing knowledge and expertise may need to balance GenAI use with traditional mentoring and deliberate practice. They will have to ensure that employees continue to develop and retain essential skills, particularly in areas where human judgment and creativity are essential (Beane & Anthony, 2024; Dell'Acqua et al., 2023). This includes developing practices that integrate both algorithmic and traditional approaches into learning and development, maintaining engagement and motivation across hierarchies, especially if senior workers and higher performers see their skill-based comparative advantages erode. The all-round availability of large, pre-trained models also raises questions about the value of proprietary data and internal capabilities relating to AI model development and deployment (Gregory, Henfridsson, Kaganer, & Kyriakou, 2021; Vomberg et al., 2023).[13] As GenAI models are widely accessible and imply low barriers to adoption, organizations may need to focus on developing complementary assets such as unique organizational processes, leadership, culture, and intangible assets that are harder to imitate or substitute in order to gain sustainable competitive advantages (Barney & Reeves, 2024; Krakowski et al., 2023).

5. Conclusions and future research

Building on the argument that GenAI represents a qualitative shift in the nature and affordances of AI as a technology, expanding beyond traditional prediction and optimization capabilities, this paper outlines four key dimensions – GenAI as a GPT, its role in catalyzing exploratory innovation, its function as a complementary cognitive artifact, and its democratizing impact – that challenge existing theoretical frameworks and organizational practices. A task-based analysis highlights significant implications for policy and practice. Based on these insights, several key themes open up new questions and promising avenues for future research, outlined in Table 2.[14] The themes and their implications are discussed in the next section, with suggestions for future research avenues.

5.1. Human-capital development and competitive strategy

GenAI challenges traditional models of human-capital development in organizations. While prior research examined how predictive AI affects specific skills through automation or augmentation in a convergent paradigm (e.g., Choudhary, Marchetti, Shrestha, & Puranam, 2025; Tschang & Mezquita, 2021), GenAI's broad applicability across convergent as well as divergent tasks necessitates revisiting or expanding task-based frameworks that have historically emphasized automation's effect on middle-skilled work (e.g., Fonseca et al., 2018). The compression effect where less experienced workers benefit disproportionately from GenAI assistance (Boussioux et al., 2024; Dell'Acqua et al., 2023) also introduces novel dynamics in organizational learning and knowledge transfer, as widespread GenAI adoption may lead to a decline in valuable, codified human training data generation (Reeves, Yin, & Simperl, 2024), which is essential for training highly performant models. This creates potential misalignment between people who are best positioned to contribute knowledge (experts or senior employees) and those who benefit most from its codification (novices or junior employees). Future research could examine how organizations can redesign learning and development practices to address these challenges, while ensuring that GenAI integration promotes distributed skill advancement and preserves pathways for developing domain expertise as well as novel, AI-specific skills. At the same time, emerging studies have found that top performers may also benefit disproportionately from GenAI (Kim, Kim, Muhn, Nikolaev, & So, 2024; Toner-Rodgers, 2024), suggesting a need to identify the contingencies and dynamics (e.g., human expertise versus GenAI model performance) that determine the distribution of benefits and whether AI automation or augmentation occurs (Qiao, Rui, & Xiong, 2025; Raisch & Krakowski, 2021).

GenAI's democratizing effects raise fundamental questions about governance mechanisms and sources of competitive advantage in organizations. While the technology itself, in line with prior research (Krakowski et al., 2023), may not constitute a sustainable advantage given its broad accessibility (Barney & Reeves, 2024), future research may examine how organizations develop complementary capabilities around GenAI deployment, such as effective management practices around leadership, culture, and human resources (Hillebrand, Raisch, & Schad, 2025; Lawrence, 2024, pp. 38–39). By lowering barriers to entry, GenAI enables smaller firms to compete with larger companies, potentially reconfiguring industry dynamics (Kenny, Kowalkiewicz, & Oosthuizen, 2024). Small-scale content creation platforms can for example leverage GenAI to compete with larger media conglomerates by offering personalized content and tailored customer experiences at a lower cost (Wessel et al., 2023). Research may also explore how human capital and digital work can evolve with hybrid agency (Feuerriegel et al., 2024), including the emergence of novel skills like prompt engineering (Robertson et al., 2024) and how these developments affect competitive dynamics and business models (Wessel et al., 2023).

5.2. Trust, explainability, human-machine interaction

Trust is essential for effective hybrid agency, as it influences adoption and acceptance of AI output and thereby determines outcomes of problem-solving tasks. GenAI raises new questions in this domain, because unlike predictive AI, which assists with

[13] For instance, the subsequently launched GPT4 outperformed the fine-tuned GPT3.5-class model "BloombergGPT" in financial tasks despite its $10 million development budget (Li et al., 2023).

[14] The table draws on the one by Bouschery et al. (2023, p. 148).

Table 2
Future research.

Theme	Level of analysis	Research questions
Human-capital development and competitive strategy	Individual Organizational	• How do GenAI's democratizing effects reshape sustainable competitive advantages, and which complementary capabilities must organizations develop? • When and how does GenAI's differential performance impact manifest in compression effects, and what are the implications for learning and skill development? • Which micro-level mechanisms make GenAI a complementary cognitive artifact and how can organizations prevent deskilling?
Trust, explainability, human-machine interaction	Individual Organizational	• How do trust dynamics differ between convergent and divergent GenAI applications, particularly given GenAI's distinctive error profile (i.e., hallucinations)? • What mechanisms can maintain GenAI's generative benefits while enabling effective output validation? • How do GenAI models' opacity and explainability impact human trust, perceptions of agency, and accountability?
Organization design, structure, and learning dynamics	Organizational	• Which mechanisms determine effective balancing of centralized control and decentralized GenAI-enabled innovation in organizations? • How do GenAI's capabilities affect firm boundaries, organizational structures, and the optimal distribution of decision rights? • How should organizations manage "shadow AI" and capture value from individual-level GenAI adoption, while maintaining strategic alignment and data security?
Science and R&D	Organizational Institutional	• What role does GenAI play in enhancing generative and impact-driven research and in addressing grand challenges, and what are its limitations? • What are GenAI's implications for knowledge representation and the potential for new scientific paradigms? • What are the limits of GenAI-created synthetic data and simulacra in advancing research, and what determines the insights' validity and reliability?
Technology development and virtualization	Technical Organizational Societal	• How will agentic AI and personal agents enabled by GenAI reshape human-AI interactions and relationships between organizations and stakeholders? • What determines effective boundaries between human and artificial agency in increasingly autonomous GenAI systems? • How should organizations approach data strategy and architectures to enable human-AI complementarity, while maintaining meaningful human involvement?
Regulation, policy, and ethics	Institutional Societal	• What ethical considerations arise from GenAI-generated content being indistinguishable from human content and how can alignment with diverse human values be achieved? • How does widespread GenAI adoption influence labor markets, task allocation, and benefit distribution, and what policies can promote inclusive growth? • How should frameworks evolve to address novel challenges in copyright, privacy, and accountability, along with risks like misinformation and existential concerns?

convergent tasks and whose abilities and limitations are comparatively better understood (Dell'Acqua et al., 2023), GenAI's qualitatively different functioning and emergent capabilities enable outputs that are indistinguishable from, or even preferable to, human-generated content (Ayers et al., 2023; Jones & Bergen, 2024). This includes the ability of generative agents to act as simulacra that in effect function equivalently to human agents (Cui et al., 2024; Park et al., 2023). This dynamic is particularly salient in divergent tasks, where blurring boundaries create novel challenges for trust and agency compared to the contemporary understanding of hybrid agency (Vanneste & Puranam, 2024). For example, unlike predictive AI's typical *false negatives* (equivalent to a type II error, e.g., failing to find a quote), GenAI's distinctive error profile introduces prevalent *false positives* (equivalent to a type I error, e.g., producing a non-existent quote) through hallucinations. This may fundamentally alter trust dynamics unless humans understand its probabilistic and generative nature. Contemporary models of algorithm aversion, where humans generally prefer human agents (Dietvorst, Simmons, & Massey, 2018; Jago, 2019), may need revision or extension, based on studies of how these trust dynamics differ for GenAI compared to predictive AI (Jussupow, Benbasat, & Heinzl, 2024).

GenAI models' opacity also raises questions about explainability and effective human-machine interaction patterns, as humans may find it difficult to grasp or derive how models arrive at their outputs, as was previously shown to be an issue with predictive AI relying on DL (van den Broek et al., 2021). While its natural language capabilities make its interface more accessible than predictive AI, its underlying operations remain equally if not more opaque, creating a tension between apparent accessibility and technical inscrutability (Bommasani et al., 2022; Raisch & Fomina, 2025).

Future research could examine how organizations can develop effective mechanisms for output validation while leveraging GenAI's generative affordances, and how different organizational contexts and human characteristics affect the development of effective cognitive representations and learning. Key areas may include investigating how factors like expertise level, personality traits, and familiarity with AI technology can inform the design of user-centered GenAI systems (Faik et al., 2024; Park & Woo, 2022). GenAI's human-like behavior and performance may promote algorithm appreciation (Logg, Minson, & Moore, 2019) or make AI's opacity functionally irrelevant unless explicitly identified as artificial (Yin et al., 2024). This includes examining trust dynamics with GenAI agents acting as interactive simulacra (Park et al., 2023) and developing mechanisms to enhance transparency, while improving human-AI hybrid agency and collaboration.

5.3. Organization design, structure, and learning dynamics

GenAI's widespread adoption has significant implications for organization design and governance. While information processing has historically shaped organizational structure (Galbraith, 1974), GenAI's nature as a GPT and its democratizing potential mean that it theoretically enables employees at all levels to engage with AI tools for divergent as well as convergent uses, possibly reshaping relationships between information flow and structural choices. Recent research for example suggests conceptualizing creative tasks as hybrid search processes with alternative configurations of human-AI co-creativity (Fang He et al., 2023; Raisch & Fomina, 2025). It potentially reduces reliance on top management or centralized expertise in strategizing and promoting innovation throughout an organization, enabling or even requiring agile decentralization processes down to the level of individual hybrid agents. Key research questions include how organizations can effectively balance decentralization with coordination needs, especially regarding strategic alignment and data security (Ellinger et al., 2024; Joseph & Sengul, 2024). Democratization may for example lead to renewed questions relating to knowledge management and "shadow IT" (Mallmann, Maçada, & Oliveira, 2018), given reports of employees widely adopting GenAI tools outside organizational mandates (Microsoft and LinkedIn, 2024).

The mechanisms through which humans learn from GenAI interaction also appear qualitatively different from those associated with predictive AI. Prompting (articulating and iterating on requests to GenAI systems) may constitute a novel form of *praxis* and meta-cognitive development, as humans need to explicitly represent and formulate existing and required knowledge and evaluate responses as possible solutions (Efklides, 2006; Porayska-Pomsta, 2016). This suggests that effective GenAI use simultaneously requires and develops domain expertise as well as novel AI-specific competencies such as prompt engineering (Robertson, Ferreira, Botha, & Oosthuizen, 2024), creating a recursive learning dynamic distinct from previous technologies.

Future research could investigate how organizations can design learning environments that promote active engagement with GenAI while maintaining sufficient domain expertise for critical evaluation of outputs, particularly given the risk of deskilling and overreliance on AI-generated solutions (Hannigan et al., 2024; Lindebaum & Fleming, 2024). Future studies may also investigate optimal approaches to algorithmic decision authority versus human discretion (Grote, Zürich, Parker, & Crowston, 2024; Hillebrand et al., 2025; Kim, Glaeser, Hillis, Kominers, & Luca, 2024), particularly given the need to maintain strategic alignment while enabling decentralized innovation through GenAI tools.

5.4. Science and R&D

Advances in AI as a GPT can potentially drive progress across multiple scientific fields, enabling breakthroughs in areas like medicine, climate science, and energy efficiency by enhancing societal capacity for problem solving and catalyzing innovation (Lawrence & Montgomery, 2024). GenAI introduces unprecedented opportunities for accelerating scientific discovery through novel forms of hypothesis generation, experimentation, and theory development (The Economist, 2023) as demonstrated in mathematics (Romera-Paredes et al., 2024) and pharmaceutics (Elbadawi, Li, Basit, & Gaisford, 2024). While predictive AI can enhance empirical analysis through pattern recognition, GenAI's ability to engage in richer knowledge representation and recombination suggests potential for more fundamental contributions to scientific understanding (Bail, 2024). In organizational theory, for example, GenAI's capacity to process and synthesize diverse concepts offers opportunities for richer theory development (Tranchero, Brenninkmeijer, Murugan, & Nagaraj, 2024). This goes beyond predictive AI's role in supporting inductive theory building through pattern recognition (Shrestha, He, Puranam, & von Krogh, 2021) to potentially enable identification of novel theoretical connections that would be difficult for human researchers to discern independently, offering new opportunities for generative and impact-driven research (Williams, Harley, Walls, Whiteman, & Dowell, 2025).

GenAI's ability to create synthetic data and simulations such as interactive simulacra of complex systems and behaviors enables new approaches to studying existing phenomena and exploring entirely new ones. It enables novel approaches to scientific inquiry, allowing researchers to explore new scenarios and experiments that would be impractical or impossible in physical settings (Park et al., 2023). Future research could examine how GenAI can be leveraged to enhance scientific discovery and R&D, particularly in addressing grand challenges beyond predictive AI's capabilities (George, Haas, & Pentland, 2014; George, Osinga, Lavie, & Scott, 2016). While opportunities span from progressing research on climate change and sustainability (Larosa et al., 2023) to modeling drug discovery (Grisoni et al., 2021) and animal language and communication (Hagiwara, 2023), questions remain about the validity and reliability of GenAI-generated insights. Research should therefore investigate how to balance the technology's potential for accelerating scientific progress through multimodal data processing and novel solution generation against methodological concerns about its propensity for plausible but potentially incorrect outputs when applied in a convergent paradigm.

5.5. Technology development and virtualization

The affordances of GenAI relating to simulation and virtualization capabilities imply a qualitative advancement in ubiquitous computing that warrants investigation across multiple research streams. First, GenAI's abilities in modeling social systems through virtual and generative agents, silicon sampling, and interactive simulacra extend beyond predictive AI's capabilities in modeling physical systems, such as digital twins used in manufacturing or product design (van Dyck, Lüttgens, Piller, & Brenk, 2023). This raises questions relating to the implications of current and emerging GenAI models for knowledge representation and related theories (e.g., Burton-Jones, Recker, Indulska, Green, & Weber, 2017).

Second, the emergence of "agentic AI" systems, defined as "AI systems that can pursue complex goals with limited direct supervision" (Shavit et al., 2023, p. 1), suggests evolution toward increasingly sophisticated autonomous agents. While predictive AI has already reached human-level performance in socially advanced games like poker and *Diplomacy* (Bakhtin et al., 2022; Brown & Sandholm, 2019), GenAI's advances in general-purpose capabilities involving emotion and theory of mind (Kosinski, 2024; Strachan et al., 2024) suggest a shift in AI capabilities, enabling more ubiquitous deployment of agentic AI for human collaboration and task delegation in real-life problem solving. These developments create research opportunities regarding how organizations can effectively leverage GenAI models for simulation and learning, what determines appropriate boundaries between human and artificial agency (Murray et al., 2021), and how technical architectures can enable human-AI complementarity while maintaining meaningful human involvement.

Research may also address current limitations and challenges. The increased deployment of sophisticated generative agents or autonomous task delegation carries risks of unpredictable behavior beyond those associated with predictive AI (Vanneste & Puranam, 2024), given that the technology's scale, rapidly increasing yet unintuitive performance, and distinctive error profile (Dell'Acqua et al., 2023). While concerns have been raised about "model collapse" from training on AI-generated data (Marcus, 2018; Shumailov et al., 2024), evidence from applications like Waymo's extensive use of simulated driving (Waymo, 2020) and AlphaGo Zero's exclusive reliance on self-play (Silver et al., 2017) suggests that training models on (exclusively) synthetic data can enable human- or superhuman-level performance. Developments in model architectures, multimodal learning, and largely untapped data sources like audio and video (Bommasani et al., 2022; Roman et al., 2022) indicate possible paths forward for continued collection and training using human-generated data.

Key research questions include how multimodal learning can expand capabilities while maintaining computational feasibility, which architectural innovations might enable more efficient training, and how organizations should approach data strategy and infrastructure investments given the power of pre-trained models and potential of synthetic data. This particularly concerns the value of internal or external data collection aimed at starting and sustaining network effects in AI-driven business models (Gregory et al., 2021; Vomberg et al., 2023).

5.6. *Regulation, policy, and ethics*

GenAI's transformative potential may imply a need to reevaluate AI ethics, particularly concerning representation of human values and preserving meaningful human agency. While contemporary discussions have focused on bias mitigation and fairness in specific applications (Glaser, Sloan, & Gehman, 2024), GenAI's general-purpose capabilities and rapid adoption suggest an even more urgent need to engage with foundational meta-ethical questions in terms of how to represent and encode diverse human values in AI systems. Prior work has shown that although certain basic values may be universally recognized, many moral perspectives are influenced by cultural and contextual factors (Awad et al., 2018), challenging the notion of AI systems being unbiased or objective (Barrowman, 2018). This complexity poses significant challenges in aligning GenAI with human values, requiring not only technical solutions but also interdisciplinary efforts to reconcile diverse moral perspectives (Klingefjord, Lowe, & Edelman, 2024). As organizations increasingly use GenAI in problem-solving processes, questions about moral responsibility, accountability, and the ethical implications of AI-generated content become more pressing (Hagtvedt, Harvey, Demir-Caliskan, & Hagtvedt, 2024). Future research may explore frameworks that ensure AI systems that support and enhance human agency rather than undermine it, addressing the primary ethical dimensions of *goal setting* and *value alignment* in GenAI deployment (Krakowski, 2021).

While offering expanded access to powerful technologies, GenAI's democratizing effects introduce regulatory challenges that demand novel governance frameworks. Increased accessibility may alleviate historical digital divides (Yu, 2020) and expand access to evidence-based reasoning (Costello et al., 2025), but also raises concerns about the concentration of power among firms controlling advanced models (Ahmed, Wahed, & Thompson, 2023) and the potential homogenization of outputs due to algorithmic feedback loops (Epstein et al., 2023). These developments require new approaches to organizational discretion and rule-making as determinants of equality in organizations (Radoynovska, 2018), particularly in balancing universal standards with local or contextual AI governance adaptations.

Additional important issues relate to privacy protection, energy consumption in model training, and societal impacts of widespread GenAI deployment (Bender et al., 2021). GenAI's ability to blur boundaries between inspiration, adaptation, and originality raises novel challenges in copyright and intellectual property law. The potential misuse of GenAI in generating misinformation or propaganda also suggests a need for accountability mechanisms that can evolve alongside technological advancements while upholding ethical principles (Epstein et al., 2023). Future research could focus on developing regulatory frameworks that address these challenges, ensuring desirable GenAI development and deployment in line with the aforementioned policy implications.

5.7. Conclusion

This paper argues that GenAI represents a qualitative shift in AI, requiring a foundational reassessment of its role in management and organizations. Moving beyond the conventional view of AI as primarily a convergent technology focused on uncertainty reduction and optimization (see Amabile, 2020), GenAI's generative capabilities in problem-solving tasks challenge theoretical frameworks that emphasize automation and efficiency (see Cabantous & Gond, 2011). Through four key dimensions – GenAI's *i) broad applicability as a GPT*, *ii) catalytic role in exploratory innovation*, *iii) function as a complementary cognitive artifact*, and *iv) democratizing effect* – this paper proposes an expanded paradigm that integrates divergent perspectives essential for supporting creativity, innovation, and human potential. This technological phase shift, characterized by emergent capabilities that enable use in both convergent and divergent tasks, *reinforces* rather than *diminishes* the importance of human agency and imagination. Ultimately, human agency rather than technological determinism will shape how these technologies are developed and applied to serve organizational and societal objectives (Brusoni & Vaccaro, 2017; Krakowski, 2021).

Realizing GenAI's potential requires a human-centered approach that places human welfare and agency at the core of design, implementation, and use (Faik et al., 2024; Krakowski, Haftor, Luger, Pashkevich, & Raisch, 2019; Shneiderman, 2022). GenAI's democratizing aspects can amplify these mechanisms, promoting creativity, innovation, and broadly shared growth when coupled with appropriate policy and managerial practices (Brynjolfsson, 2022). To achieve these benefits, careful attention to complementary human capabilities and organizational practices is central to promote effective hybrid agency that preserves human engagement, reflection, and ethical responsibility. As organizations and society adjust to this profound technological transition, deliberate choices around the enabling implementation of AI for innovation and economic growth, equitable distribution of the benefits, and human-complementary development that preserves core human values and agency will determine whether GenAI's transformative potential results in widely shared prosperity. The future of human skill development and flourishing may depend not primarily on AI's expanding capabilities, but on the ability to develop and implement approaches that leverage these capabilities in service of human-centered objectives and outcomes.

> *"What we have to do is really start seeing how creativity permeates all innovation. Whenever we're trying to create something that doesn't exist, and whenever we try to communicate with 'the other' that is not like us, that involves creativity. So all learning, all education, involves creativity. Because all of us are different, so we approach information differently. (…) Everybody's so stressed about what's going to happen with the education system when we have chatbots that allow kids to 'cheat.' Well, maybe we have to start asking, is it possible that for too long we've been rendering ourselves robotic? And we were trying to teach people things that can be too easily automated away and roboticized away? Maybe that's not really where the greatest human strength is, and maybe we really need to reconsider education that really taps into the greater depth of human creativity."*
>
> ~ Monika Bielskyte, futurist (*Object Subject Form* podcast, Season 1, Episode 5, published July 23, 2024)

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author used ChatGPT (OpenAI) and Claude (Anthropic) to enhance the crafting, language, and readability of this manuscript. After using these tools, the author reviewed and edited the content as needed and takes full responsibility for the content of the published article.

CRediT authorship contribution statement

Sebastian Krakowski: Writing – review & editing, Writing – original draft, Conceptualization.

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