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MANAGING WITH ARTIFICIAL INTELLIGENCE: AN INTEGRATIVE FRAMEWORK

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Managing with artificial intelligence (AI) refers to humans' interaction with algorithms performing managerial tasks in organizations. Two literatures exploring this interaction—human-AI collaboration (HAIC) and algorithmic management (AM)—have focused on distinct managerial tasks: while HAIC examines executive decision-making, AM focuses on managerial control. This article presents a review of both literatures to identify opportunities for integration and advancement. We observe that HAIC's and AM's micro-level emphases on different managerial tasks have resulted in diverging conceptualizations of context, agency, interaction, and outcome. Adopting a more encompassing systems lens, we unveil previously concealed linkages between HAIC and AM, suggesting that the two literatures have analyzed two sides of the same phenomenon: while HAIC explores how humans use AI to manage, AM describes how humans are managed by AI. We develop an integrative framework that elevates the viewpoint from tasks to the organizational context, from individual to collective agency, from local to systemic interaction, and from micro-level to multilevel outcomes. By employing this framework, we lay the foundations for an organizational perspective on managing with AI.

Throughout history, management has been understood as an organizational task reserved for humans. In recent years, however, we have witnessed a fundamental transition, with artificial intelligence (AI) taking on managerial tasks (Murray, Rhymer & Sirmon, 2021; Raisch & Krakowski, 2021). Managing with AI requires humans to interact with algorithms performing managerial tasks in organizations. Two literatures, human-AI collaboration (HAIC) (Lebovitz, Lifshitz-Assaf & Levina, 2022; Shrestha, Ben-Menahem & von Krogh, 2019) and algorithmic management (AM) (Curchod, Patriotta, Cohen & Neysen, 2020; Kellogg, Valentine & Christin, 2020) have explored this interaction, each focusing on a distinct managerial task. While HAIC examines managers and knowledge workers collaborating with AI on decision-making, AM focuses on workers and employees interacting with AI executing managerial control functions.

While the two literatures build theory on the use of AI for specific managerial tasks, they fail to recognize AI as an emergent general-purpose technology (Goldfarb, Taska & Teodoridis, 2023; Rathje & Katila, 2021) that gradually expands its scope from isolated tasks to broad applicability across tasks (Brynjolfsson & McAfee, 2014: 37). State-of-the-art AI algorithms like ChatGPT are used for a wide range of interdependent tasks (Bubeck et al., 2023), such as executive decision-making (Ramge & Mayer-Schönberger, 2023), managerial control (Streitfeld, 2024), and strategic planning (Olenick & Zemsky, 2023). By disregarding these interdependencies and

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the resulting collective behaviors and properties, current theories run the risk of being insufficiently specified (Cronin, Stouten & van Knippenberg, 2021; Molloy, Ployhart & Wright, 2011).

We address this problem by synthesizing HAIC and AM research through a comprehensive review of 183 empirical studies published between 2018 and 2024. We first analyze the HAIC and AM studies separately to clarify their conceptual divides (Molloy et al., 2011). This analysis shows that HAIC's and AM's micro-level emphases on different managerial tasks have resulted in diverging conceptualizations of context, agency, interaction, and outcome. HAIC research portrays executive decision-making within an enabling context, thereby emphasizing retained human agency, augmented interactions (i.e., algorithms complement managers), and improved task performance. Conversely, AM studies depict managerial control in a coercive context, in which human agency is restricted, interactions are automated (i.e., algorithms replace managers), and individuals are personally affected.

In a second step, we adopt a more encompassing systems lens (Anderson, 1999; Waldrop, 1993) to reanalyze our sample and unveil previously concealed linkages between HAIC and AM. These linkages suggest that the two literatures have analyzed two sides of the same phenomenon: while HAIC explores how humans use AI to manage, AM describes how humans are managed by AI. We develop an integrative framework that elevates the viewpoint from tasks to the organizational context, from individual to collective agency, from local to systemic interaction, and from micro-level to multilevel outcomes. By employing this integrative framework, we lay the foundations for an organizational perspective on managing with AI.

With this review, we aim to make three contributions: First, we clarify the scope and dynamics of managing with AI. By synthesizing prior work, we show that the phenomenon transcends clearly delineated task domains to permeate organizations more widely. This tendency is reinforced by AI's continuous progress as an emergent general-purpose technology. Second, our organizational perspective captures the interdependencies across task-level applications, as well as collective behaviors and properties that the existing task-level views fail to recognize. Third, the organizational perspective serves as a conceptual bridge connecting the micro-level HAIC and AM perspectives to macro-level examinations of AI's broader societal impact. Collectively, we reorient the field by providing a higher-level view that more fully unpacks managing with AI's implications for organizations and society.

MANAGING WITH AI

What Is Managing?

The scholarly perspective of management has evolved through three stages (Certo & Certo, 2019; Hitt, Middlemist & Mathis, 1989). Classical theories depicted managers as authority figures responsible for planning and organizing their subordinates' work (Fayol, 1916; Taylor, 1911). Subsequently, neo-classical theories shifted their focus toward social interaction, thereby emphasizing managers' role in leading and controlling workers (Barnard, 1938; Follett, 1941). In the modern era, a systems perspective recognized the managerial role of knowledge workers who, although lacking formal authority, make decisions that impact an organization's performance significantly (Drucker, 1967, 1974; Senge, 1990).

Integrating these perspectives, Daft (2022: 5) defined management as "the attainment of organizational goals in an effective and efficient manner through planning, organizing, leading, controlling, and [deciding on] organizational resources."[1] Consistent with the systems perspective, management is not confined to those with "command over people" but extends to everyone bearing "responsibility for contribution" (Drucker, 1974: 7). Knowledge workers are specifically responsible for contribution, as they use their "freedom to do things their own way" to make decisions that impact the effectiveness and efficiency of an organization's goal attainment (Drucker, 1967: 120). While managers impact others hierarchically through their positional authority, knowledge workers do so laterally through their knowledge authority (Drucker, 1974: 6). Management occurs in an organization, described as "a social entity that is goal-directed and deliberately structured," and applies "to all organizations, including both profit and non-profit ones" (Daft, 2022: 11). Consequently, management extends beyond business managers to include professionals such as "doctors, lawyers, teachers, accountants, [and] chemical engineers" (Drucker, 1974: 37).

[1] Daft (2022) described deciding as a core managerial task within the planning task category. Drucker (1967: 113) emphasized decision-making as "the *specific* executive task." Given decision-making's central importance in research on managing with AI, we present it as a separate task category.

Interestingly, Drucker (1967: 165) anticipated that technology would promote the decentralization of management: "With the computer's taking over computation, people all the way down in the organization will have to learn to be executives and to make effective decisions." Subsequent research provided evidence of the way technology enables managerial authority to be delegated to individual experts throughout the organization (Lee & Edmondson, 2017). Foss (2003), for instance, documented how Oticon's adoption of advanced information technology to coordinate plans and actions facilitated managerial work's decentralization. Similarly, Bernstein, Bunch, Canner, and Lee (2016) described how self-managed organizations use technology to assign decision rights and grant everyone access to the same information. Most recently, Hsieh and Vergne (2023) demonstrated how AI and blockchain technology enable decentralized autonomous organizations, like Bitcoin, which leverage algorithmic coordination, to eliminate managerial authority.

What Is AI?

Pioneers such as John McCarthy and Marvin Minsky described AI in terms of "making a machine behave in ways that would be called intelligent if a human were so behaving" (McCarthy, Minsky, Rochester & Shannon, 1955: 11). In this tradition, AI is not a specific technology, but "a moving frontier of next-generation advancements in computing" (Berente, Gu, Recker & Santhanam, 2021: 1435). In the late 1980s, for example, rule-based automation was introduced into expert systems providing managers with decision support (Yoon, Guimaraes & O'Neal, 1995). These early systems are deterministic, since they follow pre-programmed rules to perform repetitive tasks (Chalmers, MacKenzie & Carter, 2021). Berente et al. (2021: 1435) conclude that "expert systems were widely considered a type of AI then, but most would not consider it a type of AI today."

Contemporary AI differs from prior technology vintages by its ability to learn and adjust its behavior on the basis of the data to which it is exposed (Rahwan et al., 2019). Machine learning enables algorithms to learn from experience without the need for explicit human programming (Mitchell, 1997). For example, organizations use deep learning based on artificial neural networks, a type of machine learning that distinguishes itself from earlier technologies by its exceptional capacity for autonomous learning and action (LeCun, Bengio & Hinton, 2015). This capacity is crucial for management (Raisch & Krakowski, 2021), which, unlike rule-based automation, "cannot just carry out orders" (Drucker, 1967: 6) but requires autonomy over "the direction, the content, and the quality of the work or the methods of its performance" (Drucker, 1967: 6). Unlike earlier technologies, contemporary AI is distinguished by its ability to "make the rules" (Glikson & Woolley, 2020: 629) and to "learn, adapt, and act autonomously" (Baird & Maruping, 2021: 316). Consequently, we refer to contemporary AI applications that "have the capacity to learn, and can therefore improve and adapt based on experience" (Chalmers et al., 2021: 1030).

In practice, contemporary AI evolved in two waves: predictive and generative AI (Raisch & Fomina, 2025). Since the mid-2010s, predictive AI learns patterns from existing data in order to anticipate specific task domains' outcomes, such as capital investment's future returns or applicants' future job performance. The early 2020s saw the emergence of generative AI, such as generative artificial networks (GANs) (Goodfellow et al., 2014) and transformer-based large language models (LLMs) (Vaswani et al., 2017). These generative AI applications create new data based on learned patterns, which organizations apply across a wide range of task domains (Bubeck et al., 2023). For example, generative AI helps managers develop strategies, solve problems, and provide employee feedback. Collectively, predictive and generative AI have the transformational potential to create intelligence as a general systems property, rather than a specific human attribute (Townsend, Hunt, Rady, Manocha & Jin, 2023).

However, even contemporary AI systems fail to provide "strong AI" (Glikson & Woolley, 2020: 629) or "artificial general intelligence" (Bubeck et al., 2023: 1), both of which refer to futuristic visions of algorithms able to perform all tasks just as well as, or even better than, humans. Contemporary AI lacks consciousness or intrinsic motivation (Bubeck et al., 2023), therefore requiring humans to set its goals (Glikson & Woolley, 2020). Moreover, managerial tasks' computational complexity means that AI can only produce outputs that approximate reality (Fortnow, 2013). Consequently, human intuition and judgment are essential to align AI outputs with practical realities. Furthermore, data constraints can degrade AI performance, yielding biased outcomes or hindering AI application entirely (Choudhury, Starr & Agarwal, 2020). Owing to these challenges, humans remain involved in managerial processes and interact with machines on a wide range of tasks (Raisch & Krakowski, 2021).

What Is Managing with AI?

In recent years, scholars have begun to expand traditional management theories from humans to AI algorithms (Murray et al., 2021; Raisch & Krakowski, 2021). Although this emerging body of research lacks a unified definition of managing with AI, it is possible to discern common elements across studies. Collectively, these studies focus on algorithms performing managerial tasks (Lebovitz et al., 2022; Möhlmann, Zalmanson, Henfridsson & Gregory, 2021), thereby diverging from traditional management theories' exclusive attention to humans undertaking these tasks (Robbins & Coulter, 2021: 32). Furthermore, the core analytical focus is on humans' interactions with algorithms (Bucher, Schou & Waldkirch, 2021; Raisch & Fomina, 2025), whereas traditional management theories examine interactions between humans (Daft, 2022: 45). Like traditional management theories, research on managing with AI occurs within organizations (Anthony, Bechky & Fayard, 2023; Puranam, 2021).

In synthesizing this work, we define managing with AI as *humans' interaction with algorithms performing managerial tasks in organizations*. This definition includes all core managerial tasks—planning, organizing, leading, controlling, and deciding. A task is managerial if it substantially affects an organization's ability to attain its goals effectively and efficiently. Furthermore, this definition encompasses all humans who interact with AI, including managers and knowledge workers who use algorithms to manage, as well as employees and workers whom algorithms manage. These algorithms have the capacity to learn, adapt, and act autonomously, which allows them to perform managerial tasks. Lastly, our definition applies to human-algorithm interactions in all types of organizations, whether they are business firms with profit goals or public entities with non-profit goals.

REVIEW METHODOLOGY

To cover managing with AI broadly, we searched in level 3, 4, and 4* management journals listed in the Association of Business Schools' (ABS) *Academic Journal Guide*, considering the following categories: entrepreneurship, general management, human resource management, information systems, innovation, international business, marketing, organizational psychology, organizational studies, public sector management, social sciences, and strategy. We conducted our search for "artific*" AND "intelligen*" OR "algorithm*" in the keywords, abstracts, and titles of articles published in these management journals using the *Web of Science* and complemented it with extensive back-and-forward citation searches (Torraco, 2005). Overall, this search identified 5,726 articles published online until May 31, 2024.

We screened these articles using inclusion criteria that reflect our research's boundaries (Elsbach & van Knippenberg, 2020). Specifically, we derived three criteria from our definition of managing with AI. First, we only included articles that focus on managerial tasks, namely planning, organizing, leading, controlling, and deciding (Daft, 2022). While AM articles focus on managerial control, HAIC articles address decision-making broadly, which may include non-executive decisions. For HAIC articles, we therefore individually assessed whether they focused on decisions that impact organizational goal attainment significantly. Second, we only included articles of contemporary AI solutions with the ability to learn and act autonomously. If not indicated explicitly, we checked whether the article's description of the task and AI usage suggested a machine-learning application. Contemporary AI, such as deep learning with artificial neural networks, emerged in the mid-2010s (Goodfellow, Bengio & Courville, 2016). It took time for these technologies to diffuse in practice, as well as for management researchers to write papers and publish them. Consequently, the first articles in our sample are from 2018, and most others were published between 2021 and 2024. Third, we only included articles that explore the human-algorithm interaction in an organizational setting. Consistent with our definition, we considered both companies and non-profit organizations.

This process led to a sample of 270 articles (87 conceptual papers and 183 empirical studies) published between 2018 and 2024. Reading the 87 conceptual papers in our sample permitted us to form an understanding of the literature and to ensure that we covered all parts of the knowledge base. Subsequently, we focused our review on the 183 empirical studies. This allowed us to build an integrative framework emerging from the empirical evidence rather than purely from the conceptual arguments (Cronin & George, 2023). Table A.1 in the Additional Materials provides an overview of all the empirical sample studies' content and classification. While our sample analysis is limited to empirical studies, we selectively refer to conceptual papers where required to present a comprehensive view of the literature.

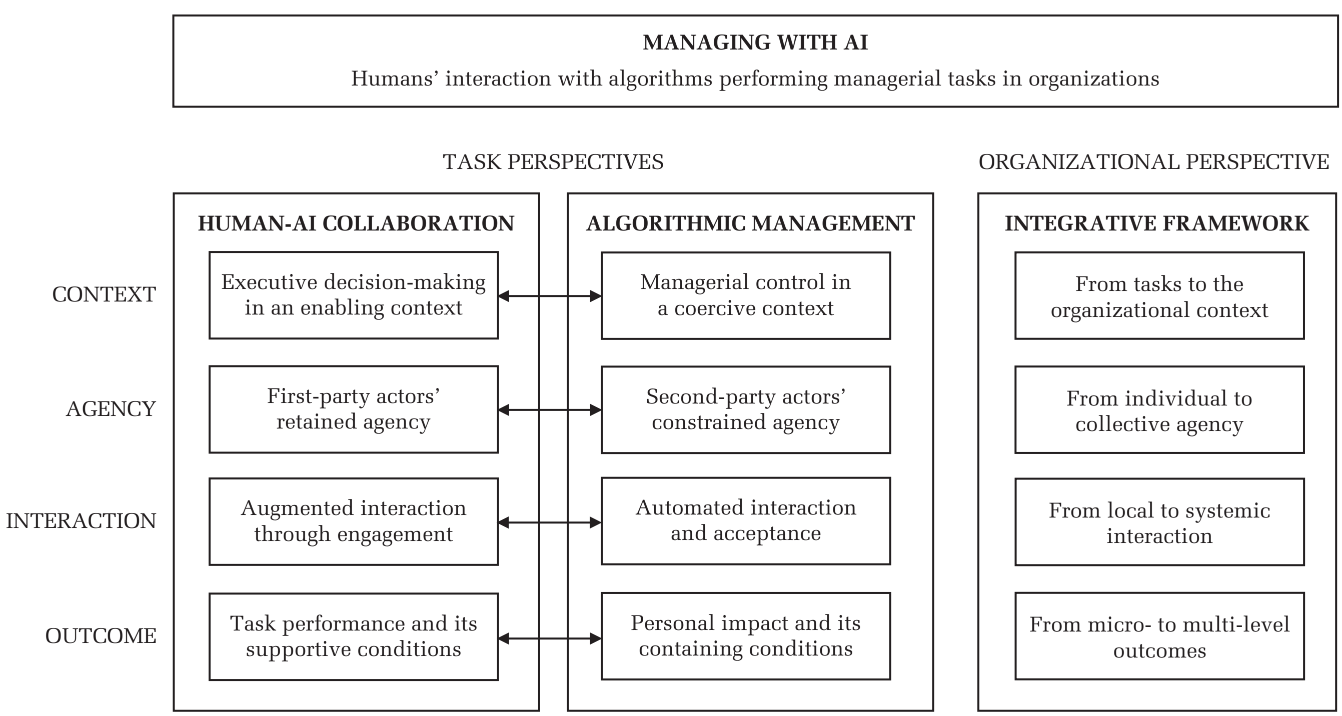
Thereafter, we coded the 183 empirical sample studies. With our coding, we strived for a "synthesis of knowledge from across research approaches in a fragmented field" (Cronin & George, 2023: 168). Such fragmentation arises when scholars employ distinct conceptual assumptions and concentrate on different parts of a larger system (Aguinis, Boyd, Pierce & Short, 2011; Cronin et al., 2021). Over the years, management scholars have underscored the importance of research bridging these divides (Cowen, Rink, Cuypers, Grégoire & Weller, 2022; Kozlowski & Klein, 2000). However, such integrative efforts are challenging due to conceptual and system-level divides' coexistence, which requires researchers to clarify conceptual divides before addressing system-level divides (Molloy et al., 2011).

Consequently, our initial coding focused on discerning diverging conceptualizations within HAIC and AM. We identified key themes in the articles to draw inferences, ran comparisons within and across the emerging themes, and concluded this process when we had assigned all the articles to at least one theme. Our initial coding produced diverging themes in respect of HAIC and AM along four dimensions: context, agency, interaction, and outcome. We then reanalyzed our sample by drawing on systems theory concepts (Holland, 1992). This approach revealed previously concealed linkages between the HAIC and AM literatures' themes, which informed our integrative framework. Overall, our coding structure contains 12 second-order themes organized into four dimensions (i.e., context, agency, interaction, and outcome) and three perspectives (i.e., HAIC, AM, and integrative). For an overview of our review that depicts the diverging HAIC and AM perspectives, as well as the integrative framework, please refer to Figure 1. Table A.2 in the Additional Materials provides the data structure, listing illustrative papers, coding frequencies, and examples of first-order codes.

THE STATE OF THE LITERATURE ON MANAGING WITH AI

The HAIC and AM perspectives provide diverging conceptualizations of managing with AI along four key dimensions: *Context* relates to the "organizational tasks and relationships" in which managing with AI occurs (Tarafdar, Page & Marabelli, 2023: 236). *Agency* signifies "a temporally embedded capacity to act with

FIGURE 1
OVERVIEW OF THE REVIEW



Two literatures build theory on the use of AI for specific managerial tasks. HAIC's and AM's micro-level emphases on different managerial tasks has resulted in diverging conceptualizations of context, agency, interaction, and outcome.

The integrative framework provides building blocks for an organizational perspective on managing with AI.

intent," which is assigned to both humans and AI algorithms (Murray et al., 2021: 552). The third dimension, *interaction*, involves a "relational exchange that takes place between humans and algorithms" (Tarafdar et al., 2023: 257). The final dimension, *outcome*, refers to the "impact of AI implementation" (Benbya, Pachidi & Jarvenpaa, 2021: 282). We proceed to review the HAIC and AM perspectives' diverging conceptualizations along these four key dimensions.

Human-AI Collaboration

HAIC research portrays executive decision-making in an enabling context, emphasizing retained human agency, augmented interactions, and improved task performance.

Executive decision-making in an enabling context. HAIC scholars draw on conceptual roots in the behavioral theory of the firm (Cyert & March 1963; Simon, 1965) and on foundational human-AI collaboration research (Engelbart, 1962; Licklider, 1960), both of which depict decision-making as the key managerial task. Consistent with these roots, HAIC scholars explore executive decision-making contexts (Fügener, Grahl, Gupta & Ketter, 2022; Lebovitz et al., 2022). Drawing on Simon (1965), Shrestha et al. (2019: 66) define decision-making as "the process of selecting the alternative that is expected to result in the most preferred outcome." Such structured decisions are the crux of most empirical HAIC studies (e.g., Selten, Robeer & Grimmelikhuijsen, 2023; Sturm, Pumplun, Gerlach, Kowalczyk & Buxmann, 2023), although there is emerging interest in AI's use for unstructured decisions requiring problem solving (Jia, Luo, Fang & Liao, 2024; see also Raisch & Fomina, 2025).

Drawing on behavioral theory foundations (March & Simon, 1958), HAIC scholars assume that executives' bounded rationality motivates human-AI collaboration in decision-making (Choudhury et al., 2020; Krakowski, Luger & Raisch, 2023). AI algorithms have information processing skills that differ from those of humans, helping organizations overcome some of their traditional cognitive limitations (Freisinger, Unfried & Schneider, 2024). AI algorithms support executive decision-making with their superior prediction skills (van den Broek, Sergeeva & Huysman, 2021, see also Agrawal, Gans & Goldfarb, 2018: 110), which reduce cognitive biases (Choudhury et al., 2020), ensure greater consistency (Bauer, von Zahn & Hinz, 2023), and provide greater speed and efficiency (Chen, Hsieh & Rai, 2022). Another AI benefit is its ability to analyze extensive datasets and identify hidden patterns (Logg, Minson & Moore, 2019, see also Rathje, Katila & Reineke, 2024). In turn, HAIC scholars assume that humans outperform AI in terms of judgment skills based on their intuition (Kesavan & Kushwaha, 2020), contextual understanding (Kim, Glaeser, Hillis, Kominers & Luca, 2024), and creativity (Jia et al., 2024).

HAIC research explores executive decision-making embedded in traditional organizational settings, such as multinational enterprises and public institutions, providing an enabling context for human–AI collaboration. Specifically, scholars analyze the decision-making structures in which humans and AI collaborate (Fügener et al., 2022; Grønsund & Aanestad, 2020; see also Choudhary, Marchetti, Shrestha & Puranam, 2023). These structures define how decision tasks are divided between humans and AI, as well as how these agents' activities are integrated. Conceptual research has further distinguished between sequential and interactive human-AI decision-making structures (Puranam, 2021; Shrestha et al., 2019). While sequential structures assign different decision tasks to humans and AI, interactive structures allow humans and AI to work jointly on the same decision task. Empirical studies provide evidence of sequential (Lebovitz et al., 2022) and interactive structures' (Metcalf, Askay & Rosenberg, 2019) use in management practice. A few HAIC studies also describe organizational-level structures that enable human-AI collaboration (Barro & Davenport, 2019), such as knowledge sharing processes (Chowdhury, Budhwar, Dey, Joel-Edgar & Abadie, 2022), high-performance work systems (Suseno, Chang, Hudik & Fang, 2022), and corporate technology centers (Goto, 2023; Pan, Froese, Liu, Hu & Ye, 2022).

First-party actors' retained agency. HAIC researchers focus on first-party actors who collaborate with AI, comprising managers (Keding & Meissner, 2021; Sturm et al., 2023) but also knowledge workers (Anthony, 2021; Faulconbridge, Sarwar & Spring, 2023) such as consultants (Strich, Mayer & Fiedler, 2021), controllers (Van Doorn, Georgakakis, Oehmichen & Reimer, 2023), accountants (Goto, 2023), physicians (Jussupow, Spohrer, Heinzl & Gawlitza, 2021), and traders (Willems & Hafermalz, 2021). Moreover, HAIC research on public management investigates civil servants (Wang, Xie & Li, 2024), while marketing scholars analyze sales experts (Habel, Alavi & Heinitz, 2024). A few scholars also examine data scientists and system developers interacting with the AI algorithms they develop (Fest, Schäfer, van Dijck & Meijer, 2023; Grønsund & Aanestad, 2020).

HAIC scholars focus on first-party actors with the expertise to complement AI. Most scholars highlight these actors' domain expertise (Pakarinen & Huising, 2023; see also Allen & Choudhury, 2022), or the "skills and knowledge accumulated through prior learning within a domain" (Choudhury et al., 2020: 1383). Such domain expertise helps mitigate AI biases by allowing humans to use their tacit knowledge, which algorithms do not have, to correct or overrule AI's predictions (Lebovitz et al., 2022). Moreover, domain expertise allows humans to complement AI's outputs (Strich et al., 2021). A few scholars also explore AI expertise, or the "skills and knowledge accumulated through prior familiarity of tasks with the technology" (Choudhury et al., 2020: 1383; see also Ahn & Chen, 2022).

Given human expertise's importance, the HAIC literature assumes that first-party actors retain their agency when collaborating with AI. While managers and knowledge workers assign some agency to AI (Shrestha, Krishna & von Krogh, 2021), they decide when to adopt AI (Ahn & Chen, 2022; Freisinger et al., 2024; Haesevoets, de Cremer, Dierckx & van Hiel, 2021), override its outputs (Chen et al., 2022; Kesavan & Kushwaha, 2020), or "mute" AI entirely (Asatiani, Malo, Nagbøl, Penttinen, Rinta-Kahila & Salovaara, 2021: 339). Rather than being subjected to AI, first-party actors are therefore described as active "users" (Bauer et al., 2023: 1582) or "partners" (Gaessler & Piezunka, 2023: 2724) remaining "in the loop" (Selten et al., 2023: 265) to form a "symbiosis" with AI (Cao, Duan, Edwards & Dwivedi, 2021: 1). Accordingly, Murray et al. (2021: 553) conceptualize "conjoint agency" as the "shared capacity between humans and non-humans to exercise intentionality." These authors further suggest that rather than losing their agency, humans who collaborate with AI increase their capacity to act with intent when performing managerial tasks.

HAIC research also suggests that first-party actors' ability to retain their agency when collaborating with AI is contingent on their levels of domain expertise. Novices with little expertise lack the absorptive capacity to collaborate effectively with AI (Choudhury et al., 2020). Anthony (2021: 1173), for example, observes that a group of young, inexperienced knowledge workers forfeited their agency to AI algorithms by "taking them for granted without understanding them." Conversely, higher levels of expertise allow first-party actors to probe AI algorithms more effectively (Lebovitz et al., 2022). Moreover, more experienced first-party actors can retain their agency and sideline AI by maintaining their work routines (Chen et al., 2022; Kim, Kim, Kwak & Lee, 2022) or by ignoring AI when they feel its advice is not helpful or is incorrect (Egala & Liang, 2023; Jussupow et al., 2021).

Augmented interaction through engagement. HAIC scholars conceptualize humans' interactions with algorithms as augmentation, defined as humans and AI collaborating to undertake a managerial task (Lebovitz et al., 2022). Augmentation is based on a complementary relationship arising from humans' and AI's different skills (Krakowski et al., 2023, see also Brynjolfsson & McAfee, 2014: 84). Complementarities emerge from humans' and AI's heterogeneous cognitive skills (Ibrahim, Kim & Tong, 2021; Waardenburg, Huysman & Sergeeva, 2022) and AI's cognitive skills and humans' social skills, which, for example, allow humans' emotions to be considered when making decisions (Huang, Rust & Maksimovic, 2019; Vorobeva, El Fassi, Costa Pinto, Hildebrand, Herter & Mattila, 2022) or when communicating decision outcomes to humans (Schuetz & Venkatesh, 2020; Strich et al., 2021).

Conceptual HAIC studies assume that executive decision-making problems require augmentation (Berente et al., 2021; Raisch & Krakowski, 2021). While AI algorithms handle levels of complexity that quickly overwhelm boundedly rational humans (Agrawal et al., 2018: 1), executive decision-making problems also "encapsulate an element of uncertainty […] rendering human input indispensable" (Jarrahi, 2018: 582). Consistent with these assumptions, empirical HAIC studies suggest that uncertainty may reduce AI's predictive accuracy (Efendić, van de Calseyde & Evans, 2020; Langer, König, Back & Hemsing, 2023), which manifests in biases associated with AI's data inputs (Choudhury et al., 2020) and outputs (Gaozhao, Wright & Gainey, 2024). Furthermore, complexity can mean that humans find AI algorithms' inputs, processing, and outputs opaque (Asatiani et al., 2021).

The HAIC literature describes various engagement practices that first-party actors use to address these problems. Engagement practices refer to interactions during which these actors integrate "AI knowledge claims with their own" (Lebovitz et al., 2022: 127). Prior research distinguishes three types of engagement practices: the envelopment of AI inputs, the auditing of AI processing, and the translation of AI outputs. Envelopment refers to first-party actors' involvement with choosing and curating training data (Asatiani et al., 2021), as well as with selecting, tuning, and governing AI algorithms (Daugherty, Wilson & Chowdhury, 2019; Krakowski et al., 2023).

Auditing describes practices that examine, validate, and correct an algorithm's processing (Anthony, 2021; Gupta, Parra & Dennehy, 2022). Both envelopment and auditing can contribute to AI quality by reducing the data and processing biases. Furthermore, translation refers to practices that make AI outputs comprehensible and actionable for users, which reduce AI's opacity (Grimmelikhuijsen, 2023; Waardenburg et al., 2022). Collectively, prior HAIC studies provide rich evidence of engagement practices, but some scholars also observe first-party actors' "disengagement practices," such as "regularly ignoring AI's input or accepting it without much reflection" (Lebovitz et al., 2022: 127).

HAIC research also provides insight into the drivers of first-party actors' engagement or disengagement. Keding and Meissner (2021) find that disengagement in the form of overreliance on AI is due to managers' strong perceptions of AI's quality, which make them trust AI blindly. Relatedly, Habel et al. (2024) show that managing expectations about AI's quality leads to first-party actors' greater engagement. Moreover, first-party actors often respond to AI opacity with disengagement practices, but those who engage subsequently create increasing transparency (Anthony, 2021; Asatiani et al., 2021; Lebovitz et al., 2022). With regard to expertise, HAIC research indicates that experts with the intuition and tacit knowledge to complement AI, ironically, tend to be the first-party actors least likely to engage with AI (e.g., Chen et al., 2022; Kim et al., 2022; Logg et al., 2019; You, Yang & Li, 2022), due to their algorithm aversion (Dietvorst, Simmons & Massey, 2015, 2018). On the other end of the spectrum, novices with little experience tend to follow AI blindly due to their cognitive overload. Lastly, AI expertise is positively related to first-party actors' willingness to engage with AI (Ahn & Chen, 2022; Choudhury et al., 2020).

Task performance and its supportive conditions. In terms of outcome, HAIC researchers are primarily interested in first-party actors' task performance. They explore their effectiveness, such as service quality (Tang et al., 2022), decision accuracy (Kim et al., 2024), and customer satisfaction (Chen et al., 2022), as well as their efficiency, such as task duration (Bader & Kaiser, 2019; Langer, König & Busch, 2021). Empirical studies comparing the task performance of humans collaborating with AI to that of humans without AI arrive at inconclusive findings, reporting increased (Chen et al., 2022; Ibrahim et al., 2021) or reduced task performance (Kesavan & Kushwaha, 2020; Kim et al., 2024), as well as mixed findings (Fügener, Grahl, Gupta & Ketter, 2021; Tang et al., 2022).

The HAIC literature also identifies supportive conditions enabling first-party actors to perform well when interacting with AI. These conditions are linked to the context, agency, and interaction dimensions. In terms of the context, Kesavan and Kushwaha (2020) find that granting first-party actors discretionary power to override algorithmic decisions reduces their overall task performance but increases it in terms of highly complex decision-making tasks. Further, Anthony (2021) provides evidence suggesting that decision-making structures enabling direct human-AI interaction are more beneficial than those only allowing indirect interaction. Relatedly, Fügener et al. (2022) find that a sequential process during which AI delegates tasks to humans is more effective than one where humans refer tasks to AI, which is due to humans' lack of sufficient meta-knowledge for making appropriate delegation decisions.

Regarding agency, the HAIC literature reports mixed findings. More experienced first-party actors tend to be better at discarding inaccurate AI advice but also often ignore correct AI advice, which can reduce their task performance (Jia et al., 2024; Jussupow et al., 2021; Logg et al., 2019). Conversely, Chen et al. (2022) show that both novices and experts increase their task performance by collaborating with AI. Lou and Wu (2021) report findings indicating that a combination of domain expertise and AI skills is required for knowledge workers to perform well when interacting with AI on innovation tasks.

Regarding interactions, Bader and Kaiser (2019) and Logg et al. (2019) provide evidence that engagement leads to a higher task performance, whereas disengagement reduces it when compared to humans working without AI. In addition, scholars show that first-party actors' perceived higher AI quality in human-AI interactions increases their task performance (Nguyen & Malik, 2022b). Relatedly, research reports that first-party actors' perceived higher AI trustworthiness is associated with a better task performance (Chowdhury et al., 2022). Nevertheless, increased explainability does not necessarily lead to a better performance in human–AI collaboration (Bauer et al., 2023).

Algorithmic Management

AM studies depict managerial control in a coercive context, in which human agency is restricted, interactions are automated, and individuals are personally affected.

Managerial control in a coercive context. While HAIC research describes executive decision-making, the AM literature explores human-AI interaction "in the context of algorithmic control" (Kellogg et al., 2020: 393), which it defines as "efforts to align worker behavior with organizational goals" (Cameron & Rahman, 2022: 39). AM studies' main conceptual roots lie in labor process theory (Braverman, 1974), which depicts work relations as a "structured antagonism" (Edwards, 1986: 5), perceiving "everything in terms of conflict and managerial efforts to control workers more completely" (Edwards, 1979: 18). Furthermore, AM studies have roots in research on technology use to control workers (Gillespie, 2014; Sewell, 1998; Zuboff, 1988, 2019). Consistent with these roots, AM research portrays "algorithmic systems as contested instruments of control" (Kellogg et al., 2020: 383).

The AM literature focuses on two main managerial control mechanisms: algorithmic monitoring and algorithmic feedback (Möhlmann et al., 2021; Tong, Jia, Luo & Fang, 2021; Vallas, Johnston & Mommadova, 2022). Algorithmic monitoring combines collecting real-time data on workers' behavior with comparing this data with the expected behavior, which serve to evaluate workers' job performance (Heiland, 2022; Qin, Jia, Luo, Liao & Huang, 2023; Wood, Graham, Lehdonvirta & Hjorth, 2019). These outputs further enable algorithmic feedback, which uses disciplinary means (i.e., fines and suspension) to sanction undesired behaviors, and enabling means (i.e., coaching and rewarding) to incentivize desired behaviors (Cram, Wiener, Tarafdar & Benlian, 2022; Höddinghaus, Sondern & Hertel, 2021; Waldkirch, Bucher, Schou & Grünwald, 2021). Parth and Bathini (2021), for example, show how a ride-hailing platform uses subtle, real-time behavioral nudges in text messages and other notifications to influence drivers' behavior and align it with the organizational goals.

Whereas HAIC research explores executive decision-making in the enabling contexts that traditional organizations provide, the AM literature primarily investigates managerial control in digital platforms' coercive context (Curchod et al., 2020; Duggan, Sherman, Carbery & McDonnell, 2022; Waldkirch et al., 2021). In these organizations, the algorithmic control systems' information processing is invisible to the workers (Huang, 2023; Möhlmann, Alves de Lima Salge & Marabelli, 2023), which is due to platforms' deliberate efforts to conceal their AI systems' inner workings (Cameron & Rahman, 2022; Veen, Barratt & Goods, 2020) and the absence of dialogue and explanation regarding the systems (Kougiannou & Mendonça, 2021; Waldkirch et al., 2021). Moreover, algorithmic control systems' opacity increases the existing information and power asymmetries between employers and workers (Curchod et al., 2020; Lavanchy, Reichert, Narayanan & Savani, 2023; Walker, Fleming & Berti, 2021). Consequently, in a conceptual study, Kane, Young, Majchrzak, and Ransbotham (2021: 389) describe algorithmic management as the relationship "between oppressor and oppressed," while Curchod et al. (2020: 667), who observed these relations empirically, depict them as "confrontational."

Second-party actors' constrained agency. While HAIC research focuses on first-party actors who use AI algorithms to manage, AM research describes second-party actors who are managed by these algorithms. These are often legally independent workers, such as ride-hailing drivers (Cram et al., 2022), food-delivery couriers (Mendonça & Kougiannou, 2023), and crowdworkers (Bellesia, Mattarelli & Bertolotti, 2023). In addition, marketing scholars are interested in sales agents (Luo, Qin, Fang & Qu, 2021) and customers (Longoni, Bonezzi & Morewedge, 2019; Reich, Kaju & Maglio, 2023), public management scholars focus on citizens (Gaozhao et al., 2024; Marjanovic, Cecez-Kecmanovic & Vidgen, 2021, 2022), and HR scholars attend to job candidates (Mirowska & Mesnet, 2022) and employees subject to algorithmic control (Malik, Budhwar, Patel & Srikanth, 2022).

Contrary to HAIC studies, actors' domain expertise plays a marginal role in AM research. Instead, the focus is on their vulnerability (Zanoni & Miszczyński, 2024), which can be due to second-party actors' socio-economic status, employment conditions, and gender. In terms of status, platform workers' often low education levels (Glavin, Bierman & Schieman, 2021) and temporary residence status (Iazzolino & Varesio, 2023; Schaupp, 2022) make these actors vulnerable to algorithmic control. Moreover, precarious employment conditions, such as dependence on a platform for work and income (Crayne & Brawley Newlin, 2024; Rahman, 2021), reliance on the state for social welfare (Peeters & Widlak, 2023), independent contractor status (Mendonça & Kougiannou, 2023), early-stage employment (Bellesia et al., 2023), and job insecurity (Duggan et al., 2022) are sources of second-party actors' vulnerability. Further, research on gender differences (Gaozhao et al., 2024) shows that fearing discrimination by human evaluators, who are perceived as favoring men, leads female second-party actors to prefer algorithmic over human evaluation (Fumagalli, Rezaei & Salomons, 2022; Pethig & Kroenung, 2023).

While HAIC scholars contend that humans retain their agency, AM scholars assume that AI algorithms "constrain human agency" (Curchod et al., 2020: 644). This assumption reflects the AM literature's roots in labor process theory, which describes workers' lack of agency in employment relations (Burawoy, 1979). Accordingly, AM scholars portray workers as "prisoners" (Curchod et al., 2020: 660) living in an "iron-cage" built by algorithms (Faraj, Pachidi & Sayegh, 2018: 68). While companies justify the use of algorithmic control as enabling workers to become entrepreneurs and enjoy greater freedom than they would have in traditional work settings, these practices actually constrain workers' already limited agency even further (Lehdonvirta, 2018; Rosenblat & Stark, 2016; Wood et al., 2019). Their constrained agency reduces second-party actors' abilities to navigate their roles, develop personal competencies, and engage in workplace activities (Duggan et al., 2022). Peeters and Widlak (2023), for example, find that citizens interacting with a state-run algorithmic system have little opportunity to report problems with the system or to object to its decisions. Accordingly, some conceptual AM studies envision a dystopian future of behavioral control that "gains steam until humans lose agency" (Kane et al., 2021: 372), effectively resulting in "the end of choice" when humans' agency is muted entirely (Lindebaum, Vesa & Den Hond, 2020: 257).

Some empirical AM studies also suggest that second-party actors are, under certain conditions, able to reduce these algorithmic constraints and reclaim agency (Cameron, 2024; Curchod et al., 2020; Weiskopf & Hansen, 2023). However, scholars emphasize that second-party actors' ability to reclaim agency decreases over the labor process's subsequent stages and when companies take retaliatory measures, while continuous changes made to algorithmic systems constrain this ability even further (Cameron & Rahman, 2022; Rahman, Weiss & Karunakaran, 2023; Tarafdar et al., 2023). Furthermore, AM scholars observe that platform workers' vulnerability (Duggan et al., 2022; Pulignano, Grimshaw, Domecka & Vermeerbergen, 2024; Schaupp, 2022) and dependence on a platform (Mendonça & Kougiannou, 2023; Rahman, 2021) reduce their ability to reclaim agency.

Automated interaction and acceptance. While the HAIC literature conceptualizes human-AI interaction as augmentation, the AM literature describes it as automation, or as replacing humans with AI algorithms in a managerial task (Anicich, 2022; Curchod et al., 2020; Qin et al., 2023). Huang (2023: 188), for example, states that "managing activities are transferred from humans to sophisticated algorithmic technological systems [and] management is no longer a human practice, but a process embedded into technology." The "absence of hierarchical reporting relationships" characterizes automated interactions (Duggan et al., 2022: 4469), while "discretionary feedback, reviews and ratings […] are calculated, interpreted and rendered actionable by [the] largely inscrutable and opaque processes of automation" (Alacovska, Bucher & Fieseler, 2024: 164).

Similar to HAIC scholars, AM scholars identify AI opacity as a defining characteristic for humans' interaction with algorithms (Rahman, 2021). However, while HAIC scholars understand opacity as a starting condition, which can partially be overcome by first-party actors' interactions with AI (Anthony, 2021; Asatiani et al., 2021), AM scholars describe opacity as an AI characteristic that organizations implement strategically or accept willingly in order to reinforce information asymmetries and to control their workers (Mendonça & Kougiannou, 2023). AI opacity creates uncertainty for second-party actors regarding their performance's measurement and the consequences of not following instructions, thereby eliciting their compliance (Gregory, 2021; Veen et al., 2020). Furthermore, AI opacity constrains these actors' learning (Gallagher, Gregory & Karabaliev, 2024; Rahman, 2021).

While HAIC research describes first-party actors' engagement, AM research focuses on second-party actors' acceptance (Möhlmann et al., 2021; Pignot, 2023; Tarafdar et al., 2023).[2] Acceptance practices allow workers to adapt their behavior to comply with algorithmic control. Bucher et al. (2021: 53), for example, observe an online talent marketplace's distinctive acceptance practices, which include "staying under the radar" (i.e., refraining from voicing concerns), "purposefully curtailing outreach" (i.e., avoiding difficult clients who could give bad ratings), "keeping emotions in check" (i.e., suppressing negative emotions), and "undervaluing work" (i.e., lowering the hourly rates to improve clients' ratings). AM studies describe acceptance as the dominant response to algorithmic control (e.g., Kougiannou & Mendonça, 2021; Liu, 2023; Veen et al., 2020) but also provide evidence of resistance, which refers

[2] As a notable exception, Cameron (2024: 461) describes workers' "engagement tactics" in AM.

to practices allowing workers to block or bypass algorithmic functions by, for example, logging off strategically (Möhlmann et al., 2021), refusing or canceling requests (Bucher et al., 2021), ignoring instructions (Tarafdar et al., 2023), using wrong identities (Iazzolino & Varesio, 2023), and communicating outside the algorithmic system (Curchod et al., 2020).

AM research also offers insight into the conditions under which second-party actors accept or resist algorithmic control (Cameron, 2024; Heiland, 2024). This work focuses on these actors' perceptions of AI's legitimacy, quality, and trustworthiness (Ochmann, Michels, Tiefenbeck, Maier & Laumer, 2024; Wang, Guo, Zhang, Xie & Chen, 2023; Wenzelburger, König, Felfeli & Achtziger, 2024). AI algorithms are perceived as legitimate when their actions are desirable, proper, or appropriate within some socially constructed system of norms, values, beliefs, and definitions (Martin & Waldman, 2023). Second-party actors' positive AI legitimacy perceptions are associated with acceptance, whereas their negative ones are linked to resistance (Raveendhran & Fast, 2021; Reid-Musson, MacEachen & Bartel, 2020; Wiener, Cram & Benlian, 2023). Besides legitimacy, low perceptions of AI quality trigger resistance through gaming and workaround tactics (Cameron & Rahman, 2022; Tarafdar et al., 2023). AM scholars also explore second-party actors' perception of AI's trustworthiness (Wesche, Hennig, Kollhed, Quade, Kluge & Sonderegger, 2024), defined as their expectation that algorithms are sufficiently competent and benevolent to rely on them (Keding & Meissner, 2021). AI trustworthiness is associated with acceptance of algorithmic monitoring (Raveendhran & Fast, 2021) and feedback (Höddinghaus et al., 2021).

Personal impact and its containing conditions. While HAIC studies focus on task performance outcomes, AM studies are primarily interested in human-AI interactions' personal impact on second-party actors. These studies focus on job-related, career-related, and psychological impacts. Job-related impacts include second-party actors' job satisfaction (Malik, de Silva, Budhwar & Srikanth, 2021; Norlander, Jukic, Varma & Nestorov, 2021; Uzunca & Kas, 2023), commitment (Malik et al., 2021, 2022; Tomprou & Lee, 2022), and engagement (Dutta, Mishra & Tyagi, 2023). Career-related impacts refer to these actors' capability development and career success (Cameron, 2024; Duggan et al., 2022; Holm & Lorenz, 2022). Finally, psychological impacts include anxiety (Bellesia et al., 2023; Curchod et al., 2020; Waldkirch et al., 2021), feelings of social isolation (Glavin et al., 2021; Walker et al., 2021), and diminished well-being (van Doorn & Chen, 2021; Wood et al., 2019).

The AM literature focuses on algorithmic control's negative personal impact (e.g., Bellesia et al., 2023; Holm & Lorenz, 2022). AM scholars have, for example, found that algorithmic control practices' adoption reduces second-party actors' employee commitment due to their perception of AI algorithms as reductionist, unfair, and impersonal (Tomprou & Lee, 2022). However, a few AM studies have also reported a neutral or positive personal impact (e.g., Dutta et al., 2023; Raveendhran & Fast, 2021). Owing, for example, to AI's greater ability to provide personalized attention and feedback, the adoption of algorithmic control practices can lead to similar or increased levels of employee commitment (Malik et al., 2021) and perceived job satisfaction (Norlander et al., 2021).

Whereas HAIC studies identify supportive conditions for first-party actors' task performance, AM researchers focus on containing conditions that reduce algorithmic control's negative impact along the context, agency, and interaction dimensions. Regarding the context, Wiener et al. (2023) find that enabling AI control practices (i.e., advice) increases employee commitment, whereas constraining AI control practices (i.e., sanctions) decreases it. Uzunca and Kas (2023) report similar findings regarding Uber drivers' job satisfaction. Holm and Lorenz (2022) observe that first-party actors in highly skilled jobs generally experience enabling AI contexts, which allow them to build new capabilities, whereas second-party actors in low-skilled jobs face constraining AI contexts that hinder their capability's development.

In terms of agency, Bellesia et al. (2023) show that established platform workers experience less anxiety than newcomers, who are more vulnerable due to their lack of positive reviews. Similarly, Glavin et al. (2021) find that their lower socio-economic status and education levels make platform workers more prone to social isolation. On the positive side, Luo et al. (2021) report that algorithmic feedback enables second-party actors' capability development; this increases even more when human feedback is added to the algorithmic feedback to reduce these actors' algorithm aversion and cognitive overload, which would otherwise obstruct their learning. Furthermore, greater AI transparency can reduce workers' negative emotions, such as anxiety (Curchod et al., 2020; Rahman, 2021; Tarafdar et al., 2023), and help them develop their competencies, both of which enable them to pursue new career opportunities (Duggan et al., 2022).

With respect to interaction, studies associate second-party actors' perceived AI legitimacy with their job satisfaction. Newman, Fast, and Harmon (2020), for example, show that workers' AI legitimacy perception mediates algorithmic practices' negative effect on their commitment. Relatedly, Wiener et al. (2023) find that AI legitimacy has a direct positive effect on employee commitment. Lastly, Lee (2018) demonstrates that if second-party actors perceive AI's legitimacy and trustworthiness as strong, they experience fewer negative emotions.

AN INTEGRATIVE FRAMEWORK OF MANAGING WITH AI

Our initial review suggests that HAIC and AM analyzed different parts of managing with AI. This practice led to fragmented and partly contradictory micro-level perspectives. Such micro-level views are reductionist since organizational phenomena cannot be fully understood by analyzing their isolated parts (Holland 1992; Holling, 2001). Micro-level views fail to explain how these parts interact at a higher level (Molloy et al., 2011) and cannot capture the collective behaviors and properties emerging from these interactions (Anderson, 1999). We therefore draw on systems theory to reanalyze our sample with a focus on making latent linkages between the HAIC and AM perspectives visible. Specifically, we use key systems concepts—hierarchy, interconnectivity, emergence, and scale (Anderson, 1999; Waldrop, 1993)—to develop building blocks that bridge the two perspectives. This integrative framework redirects scholarly attention from tasks to the organizational context, from individual to collective agency, from local to systemic interaction, and from micro- to multilevel outcomes.

From Tasks to the Organizational Context

Our initial coding revealed that the HAIC and AM literatures analyze human-AI interaction in different, clearly delineated task contexts—while HAIC research describes executive decision-making, AM research depicts managerial control. Conversely, systems theory's *hierarchy* concept recognizes that systems comprise multiple layers of subsystems (Anderson, 1999; Waldrop, 1993: 169). These subsystems interact with one another and contribute collectively to the system's functioning. Informed by the hierarchy concept, we reanalyzed our sample to explore whether the executive decision-making contexts that HAIC scholars describe, and the managerial control contexts that AM scholars depict, could be linked within a larger organizational system. In the following paragraphs, we present evidence that (1) these task contexts overlap, (2) there are interactions between them, and (3) they are connected to, and interact with, other managerial task contexts.

First, our sample analysis shows that task contexts overlap, allowing the control and decision-making to occur within the same organizational system. While HAIC scholars investigate human-AI decision-making, some also note the coexistence of algorithmic control (e.g., Chen et al., 2022; Grønsund & Aanestad, 2020; Meijer, Lorenz & Wessels, 2021). In a study of predictive policing, for example, Waardenburg et al. (2022) mention that algorithmic control enables data to be collected on suspects and criminals, which police officers, in collaboration with AI, use to make decisions. Conversely, AM scholars explore control, but many mention that decision-making also occurs in the same system (e.g., Bankins, Formosa, Griep & Richards, 2022; Bucher et al., 2021; Fumagalli et al., 2022). Parth and Bathini (2021), for example, focus on how AM collects data but also note that such data are used for making decisions about workers. Furthermore, while many AM studies explore digital platforms' "extreme case" (Wiener et al., 2023: 483), those that focus on traditional organizations, such as multinational companies and public institutions, analyze algorithmic control in the same contexts as HAIC scholars, for example, talent acquisition (i.e., Langer et al., 2021 on HAIC; Langer, König & Hemsing, 2020 on AM) or medical diagnosis (i.e., Lebovitz, Levina & Lifshitz-Assaf, 2021 on HAIC; Longoni et al., 2019 on AM).

Second, our sample analysis shows that there are interactions across these task contexts. From a HAIC perspective, Meijer et al. (2021: 844) observe that AI-based predictive policing systems are not only used for decision-making but are also applied to track police officers' reactions by means of a "surveillance logic to ensure organizational compliance" (see also Teodorescu, Morse, Awwad & Kane, 2021; Monod, Mayer, Straub, Joyce & Qi, 2024). AM research provides complementary evidence of algorithmic control's impact on decision-making (van Doorn & Chen, 2021; see also Lindebaum et al., 2020). Möhlmann et al. (2021), for example, describe how Uber drivers' attempts to game the data collected through algorithmic control trigger decisions to sanction or nudge these drivers to change their behavior, which, in turn, feed dynamically back to algorithmic control.

Third, there is also evidence suggesting that the decision-making and control contexts are connected to, and interact with, AI applications in other managerial task contexts. Both HAIC (Lin, Shao & Wang, 2022;

Maragno, Tangi, Gastaldi & Benedetti, 2023) and AM studies (Crolic, Thomaz, Hadi & Stephen, 2022; Dutta et al., 2023) describe the use of AI-based conversational agents. While these studies describe human-AI interaction on either decision-making or control tasks, they also show that "chatbots" can complement or substitute humans in communicating tasks. Maragno et al. (2023), for example, show how a chatbot analyzes citizens' requests and communicates with them by responding to their requests. In addition, Möhlmann et al. (2021) describe AM practices that combine both controlling and organizing (i.e., coordination) tasks.

Collectively, these insights suggest that humans can interact with AI algorithms across multiple managerial task contexts within the same organization. From an integrative view, scholars should therefore extend their perspective from isolated tasks to the organizational context. While systems have multiple hierarchical levels, organizations are management scholars' fundamental level of analysis (Molloy et al., 2011). Exploring organizational contexts allows these scholars to consider managerial AI applications as a whole. This is important, since different AI applications could be interrelated, for example, because the same AI systems, input data, and enabling or coercive contexts could affect multiple applications. Consequently, redirecting the scholarly perspective from individual tasks to the larger organizational contexts is the first building block of our integrative framework.

From Individual to Collective Agency

Our initial review showed that the HAIC and AM literatures conceptualize agency in terms of distinct actors interacting with AI. HAIC research describes first-party actors who retain their agency, while AM scholars depict second-party actors whose agency AI constrains. Both literatures conceptualize individual agency, or one type of human agency in interaction with AI. In contrast, systems theory's *interconnectivity* concept recognizes that, in a social system, different types of agents connect and interact with one another (Anderson, 1999; Waldrop, 1993: 145). Consequently, organizational behaviors emerge from heterogeneous agents' collective actions rather than from individual agents' actions. When we reanalyzed our sample, we took the interconnectivity between different types of actors involved with managing with AI into consideration. We found evidence suggesting that (1) first- and second-party actors are connected, (2) the same actors can have dual agencies, and (3) these actors are connected to third-party actors.

First, first- and second-party actors are connected. Several HAIC studies specify that first-party actors' collaboration with AI uses data obtained from second-party actors (e.g., Chen et al., 2022; Choudhury et al., 2020; Waardenburg et al., 2022). Grønsund and Aanestad (2020), for example, describe how knowledge workers (the first-party actors) at a shipbroker collaborate with an AI algorithm to make decisions, while the same algorithm collects data and monitors ship owners' (the second-party actors) activities in real time. Moreover, at the U.S. Patent and Trademark Office, Choudhury et al. (2020) observe that patent applicants' (the second-party actors) strategic gaming of the input data influences knowledge workers' (the first-party actors) decisions made in interaction with AI. In turn, in the AM literature, some scholars acknowledge human managers' presence and influence on second-party actors (e.g., Curchod et al., 2020; Möhlmann et al., 2021; Tong et al., 2021). While first-party agency is generally hidden in AM research, Pignot (2023: 153) cautions that "it is becoming increasingly difficult to ignore the human hand in the steering of algorithms." Multiple studies specify that second-party actors can contact first-party actors to challenge their decisions (Asatiani et al., 2021; Cameron & Rahman, 2022; Newlands, 2021). In a study of food-delivery platforms, Veen et al. (2020: 399), for example, conclude that what they observed is "purportedly an algorithmic control process" but that decisions to deactivate drivers "were shaped by managerial decision-making—a critical detail obscured from [the] workers."

Second, reanalyzing our sample also showed that humans can have dual agencies. In these cases, the same person assumes both the first-party and the second-party roles. In HAIC research, this occurs when knowledge workers collaborating with AI are simultaneously subjected to algorithmic control of their activities (Chen et al., 2022; Meijer et al., 2021). In AM research, Newlands (2021: 725) mentions "rider captains" at a food-delivery platform who wear two hats: as "riders," they are second-party actors subjected to algorithmic control, while as "captains," they are first-party actors interacting with AI on managerial tasks, such as monitoring, motivating, and providing less experienced riders with feedback. Furthermore, some AM studies describe scenarios where workers subjected to algorithmic control also interact with the AI algorithm to conduct managerial tasks (Malik et al., 2022; Tong et al., 2021). Luo et al. (2021), for example, observe the use of algorithmic management not only to control sales agents, which describes their second-party agency, but to also support these sales agents when making important sales decisions, which indicates their first-party agency.

Third, first- or second-party actors are connected to third-party actors. In the HAIC literature, some studies show that interactions between first-party actors (who collaborate with AI) and internal third-party actors (who do not), such as senior or project managers, affect the first-party actors' interactions with AI (Kesavan & Kushwaha, 2020; Waardenburg et al., 2022; see also Berente et al., 2021). Furthermore, Mead and Neves (2022) propose that external third-party actors, such as activists, media, and industry experts, might engender first-party actors' resistance to managerial AI applications. In AM research, authors describe how customers act as third parties by evaluating workers, which affects these workers' response to AI (Bucher et al., 2021; Cameron & Rahman, 2022; Rahman, 2021). AM studies, for example, report that some resistance practices have effects through workers' communication with customers who influence their evaluations (Bucher et al., 2021; Curchod et al., 2020).

Overall, these insights indicate that, in human-algorithm interaction, agency is more complex than current dominant conceptualizations suggest. From an integrative view, scholars should therefore redirect their attention from individual to collective agency. This means that different, interconnected forms of agency constitute managing with AI. Exploring agency at the collective level is important, since different types of actors might interact with the same AI system, and these actors might have social interrelations that affect their interaction with AI. These insights inform the second building block of our integrative framework, which captures the collective agency that characterizes managing with AI.

From Local to Systemic Interaction

In addition, our initial review clarified that the HAIC and AM literatures conceptualize human-AI interaction differently: while HAIC research describes augmented interaction, AM scholars focus on automated interaction. Both literatures conceptualize local interaction, or a specific type of interaction situated in space and time. Conversely, systems theory's *emergence* concept suggests that different interaction types' interplay within a system leads to novel behaviors (Anderson, 1999; Waldrop, 1993: 88). These emergent behaviors cannot be traced or attributed to any specific type of interaction. Reanalyzing our sample based on the emergence concept led to evidence suggesting that augmentation and automation are human-algorithm interactions that (1) coexist at the same level, (2) are nested across levels, and (3) are connected across time.

First, our sample analysis reveals that augmentation and automation coexist at the same level. Several HAIC scholars studying augmentation observe that some first-party actors exhibit behaviors closer to automation (Haesevoets et al., 2021; Jussupow et al., 2021). Lebovitz et al. (2022: 127), for example, "concentrated on (an) augmentation scenario" when studying the use of AI for medical diagnosis, but found that some radiologists simply accepted the algorithm's recommendations. Referring to these physicians, Lebovitz et al. (2022: 142) conclude that "what looks like augmentation on paper is much closer to automation." Automated and augmented interactions' coexistence led to different behaviors across radiologists and departments. Conversely, AM scholars focus on automation but sometimes also observe augmentation (Bucher et al., 2021; Liu, 2023; Malik et al., 2022). Tong et al. (2021), for example, describe how a financial services company optimized its call center employees' behaviors by providing experienced employees with automated AI feedback, while augmenting the AI feedback with human feedback to overcome novices' algorithm aversion.

Second, augmentation and automation are nested across levels. In HAIC research, some scholars acknowledge that augmentation contains automation at a lower level of analysis (Efendić et al., 2020; Fügener et al., 2022). Tang et al. (2022), for example, establish a link between automation at the task level and augmentation at the role or job level. They analyze "how intelligent machines can augment employee effectiveness" (Tang et al., 2022: 1022) and suggest that one way of doing so is for "machines [to] alleviate [a] burden by autonomously taking on routine *tasks* associated with the employee's *role*" (Tang et al., 2022: 1024; italics added). In AM research, some scholars observe that, at a higher level of analysis, automation is associated with augmentation (e.g., Fumagalli et al., 2022; Malik et al., 2022; Tong et al., 2021). Höddinghaus et al. (2021: 2), for example, explain that specific tasks' automation, which they investigated in their study, is nested within a larger augmentation logic, in which algorithmic management is merely "a complement to human-human leadership."

Third, we found evidence that automation and augmentation are connected across time. In HAIC research, Waardenburg et al. (2022) document that the Dutch police moved from automation to augmentation. When first-party actors found it difficult to interpret the automated AI systems' outputs, the Dutch police transitioned to an augmentation approach, which altered these actors' behavior and practices (see also Grønsund & Aanestad, 2020; Marabelli, Newell & Handunge, 2021). Others show that organizations initially engage in augmentation to explore new decision situations but transition to automation when these situations are well understood (Choudhury et al., 2020; Kesavan & Kushwaha, 2020; see also Verganti, Vendraminelli & Iansiti, 2020). In AM research, Raveendhran and Fast (2021: 12) suggest that algorithmic management involves "a human-technology combination that lies on a continuum from little to complete automation" at different stages of the process. Luo et al. (2021) report that shifting temporarily from automation to augmentation allowed a fintech company to mitigate second-party actors' resistance to AI.

Overall, these insights suggest that different types of human-AI interaction coexist and affect one another within and across space and time. From an integrative view, scholars should therefore redirect their focus from local to systemic interaction, which will allow them to consider different interaction types and the emergent behaviors they create. This systemic conceptualization of human-AI interaction is important because organizations exhibit behaviors that isolated interactions cannot explain. Our integrative framework's third building block is, therefore, systemic interaction.

From Micro- to Multilevel Outcomes

Lastly, our initial review showed that the HAIC and AM literatures focus on different outcomes. While HAIC research is primarily interested in how first-party actors' interactions with AI affect their task performance, AM scholars focus on human-AI interactions' personal impact on second-party actors. While these literatures describe specific, micro-level outcomes, systems theory's *scale* concept considers outcomes across multiple levels (Anderson, 1999). Since each scale has its own dynamics, interactions, and emergent behaviors, their outcomes also vary across levels and are, therefore, not fully predictable (Waldrop, 1993: 291). The latter is due to open systems interacting with and being influenced by their environment. Consequently, different outcomes arise at the micro, meso, and macro levels (Molloy et al., 2011). Reanalyzing our sample by keeping the scale in mind contributed insights into managing with AI's (1) meso-level outcomes, (2) macro-level implications, and (3) cross-level consequences.

First, while most HAIC and AM studies focus on micro-level outcomes, some also report meso-level outcomes. In the HAIC literature, studies provide evidence of human-AI collaboration also leading to larger, organizational-level reconfigurations and role changes (e.g., Chowdhury et al., 2022; Maragno et al., 2023; Waardenburg et al., 2022). In a global ship brokering company's longitudinal case study, for example, Grønsund and Aanestad (2020: 2) report that the adoption of human–AI collaboration not only changed individual actors' micro-level tasks and roles but also led to the "emergence of new tasks, roles, and capabilities" as well as to the "ongoing reconfiguration of the work" at the organizational level. In AM research, Höddinghaus et al. (2021) found that second-party actors' perception of AI leadership agents' trustworthiness affects their organizational attractiveness perception.

Second, there is also limited evidence that managing with AI could have implications beyond organizations. In the HAIC literature, Faulconbridge et al. (2023) document the field-level outcomes of lawyers' and accountants' interactions with AI. They rework the boundaries of their professions as a whole by, for example, collaborating with other professional groups, like technologists, when performing their tasks. In the AM literature, Holm and Lorenz (2022) find that using AI for managerial tasks increases labor market inequalities by augmenting human capabilities used in highly skilled jobs while having adverse impacts on less skilled jobs, such as constraining employees and hindering their capability development.

Third, a few studies provide insight into cross-level consequences. Sun and Medaglia (2019) studied human-AI interaction in China's public healthcare system. The authors noted that stakeholders at the micro (i.e., doctors), meso (i.e., senior managers), and macro levels (i.e., policymakers) had different, and partly contradictory, perceptions of AI adoption's impact. Asatiani et al. (2021: 326) describe how, when using human-AI interaction, a Danish public organization endeavored to achieve "instrumentally oriented outcomes," such as improved task performance, at the micro level. However, diverse stakeholders' expectations required the organization to also "cater to humanistic outcomes by making sure that the use of [AI] models would not […] harm people affected by the models' use" (Asatiani et al., 2021: 326). The use of envelopment practices helped this public organization prevent "harmful consequences," such as "widely unpredictable outcomes" (Asatiani et al., 2021: 339). In the AM literature, Lambrecht and Tucker (2019) demonstrated that advertising algorithms destined to optimize cost effectiveness at the micro level produced campaigns intended to be gender neutral but which were, instead, biased, because it is more expensive to show ads to women than to show them to men. The authors also suggest that these effects spill across digital platforms and industry sectors, leading to a discriminatory outcome at the macro level.

To conclude, HAIC and AM studies provide latent linkages suggesting that AI applications in management might have different, and partly unintended, outcomes across the micro, meso, and macro levels of analysis. From an integrative viewpoint, scholars should therefore redirect their attention from a narrow perspective on specific micro-level outcomes to a wider conceptualization spanning different outcomes across multiple levels of analysis. This wider conceptualization takes into consideration that organizations are open systems and that their actions could have different effects on a great variety of stakeholders within and beyond organizations. Consequently, the fourth and final building block captures managing with AI's multilevel outcomes within and beyond organizations' boundaries.

REDIRECTING RESEARCH TOWARD AN ORGANIZATIONAL PERSPECTIVE ON MANAGING WITH AI

Our review showed that the HAIC and AM literatures' micro-level emphases on different managerial tasks have resulted in diverging conceptualizations of context, agency, interaction, and outcome. Adopting a more encompassing systems lens enabled us to reveal previously concealed linkages between these literatures. While our integrative framework provides building blocks for an organizational perspective, it is limited to empirical findings derived from studies that did not take such an integrative perspective. Since this is a typical limitation of reviews that integrate across fragmented fields, Cronin and George (2023: 173) proposed that redirecting research also requires "disciplined imagination to develop new kinds of ideas that are necessarily speculative out of current knowledge," which helps direct future research toward "aspects of the domain in need of more frontline empirical work."

Following this advice, we conclude our research by integrating the review's empirical findings with conceptual AI papers' complementary insights. Building on this foundation, we revisit our integrative framework's four dimensions: organizational context, collective agency, systemic interaction, and multilevel outcomes. For each dimension we engage in disciplined imagination to develop new ideas (Cronin & George, 2023) by means of three steps (see Figure 2). First, we clarify managing with AI's scope and dynamics by highlighting technological developments that explain why AI increasingly penetrates organizations. Second, we identify managing with AI's key organizational processes—institutionalization, hybridization, systematization, and societal integration—capturing interdependencies across task-level applications and their resulting collective properties. Third, we redirect scholarly attention toward an organizational perspective by proposing avenues for future research.

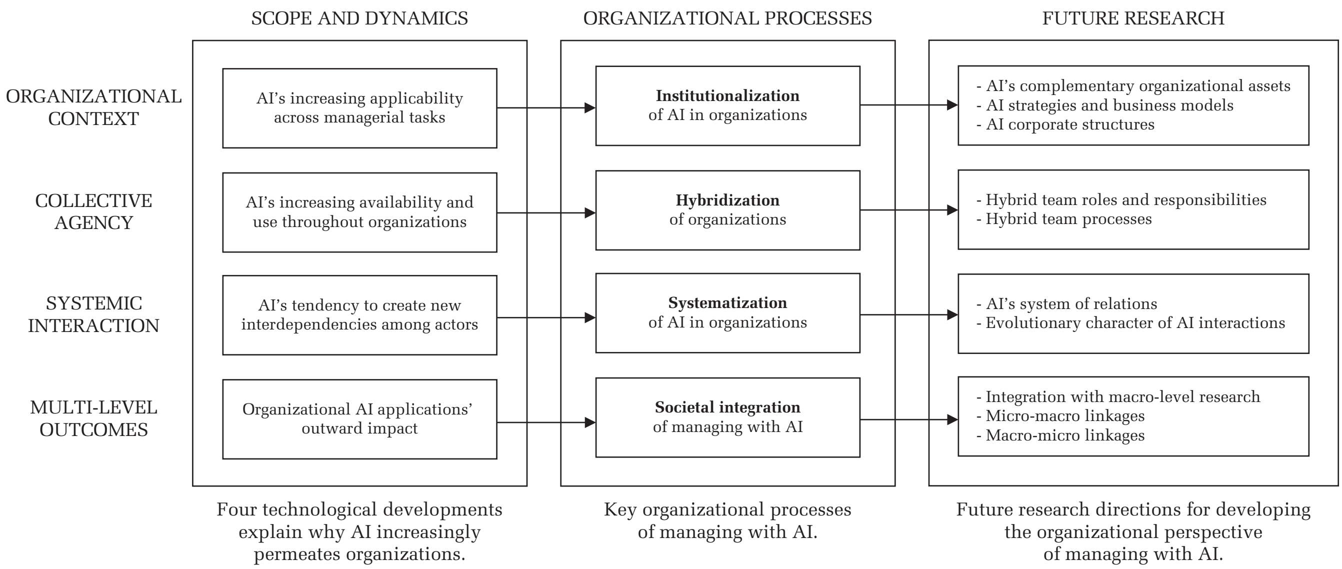
Organizational Context

Our integrative framework revealed that managing with AI can span two or more interdependent task contexts within the same organization. To capture the phenomenon of managing with AI more completely, scholars should therefore extend their perspective from isolated tasks to the organizational context.

Scope and dynamics. Scholars describe AI as a general-purpose technology (Goldfarb et al., 2023; Rathje & Katila, 2021) that constantly enables new task applications by means of technological progress (Berente et al., 2021; Brynjolfsson & McAfee, 2014: 37).[3] Early AI applications in management were limited to specific tasks (Raisch & Fomina, 2025). However, state-of-the-art AI systems, such as generative AI, are no longer constrained to specific applications and can be applied across a wide range of tasks (Bubeck et al., 2023; Mollick, 2022). Managers apply generative AI for planning, such as analyzing competitors and developing business models (Olenick & Zemsky, 2023); when organizing, such as designing job roles (Zhang & Parker, 2023); and for innovating, such as idea generation (Boussioux, Lane, Zhang, Jacimovic & Lakhani, 2024). They also use it for deciding, such as framing decisions, generating alternatives, and selecting between them (Ramge & Mayer-Schönberger, 2023); when leading, for example, for

[3] There is an ongoing debate whether AI should be classified as a "true" general-purpose technology (Goldfarb et al., 2023) or as a "junior" one (Rathje & Katila, 2021). While this debate concerns technology's cumulative economy-wide impact, our argument about its applicability across tasks is consistent with both perspectives.

FIGURE 2
ORGANIZATIONAL PERSPECTIVE ON MANAGING WITH AI



mentoring employees (Piskorski & Joshi, 2023); and when controlling, such as conducting performance evaluations (Streitfeld, 2024).

Organizational process. We expect AI's increasing applicability across managerial tasks to lead to *institutionalization*, or the process of embedding AI systematically into an organization's strategies, structures, and practices. Through this process, AI becomes a core component of the organization's functioning, rather than just a set of isolated or ad hoc initiatives. The reason for this development is that capturing value from general-purpose technologies like AI requires organizations to develop complementary assets (Goldfarb et al., 2023). Building these assets demands "large intangible investments and a fundamental rethinking of the organization" (Brynjolfsson, Rock & Syverson, 2021: 334). Companies put AI at the center of their businesses by building AI visions and capabilities, by transforming business processes, and by developing data-driven cultures at the enterprise level (Davenport & Mittal, 2023a: 27). Rather than designing one AI model for one task application, these companies establish "a unified approach that can be replicated across the company" (Davenport & Mittal, 2023b: 124). Eventually, institutionalization creates organizational contexts for managing with AI that affect many task applications throughout an organization.

Future research. AI's institutionalization in organizations reveals important avenues for future research. First, scholars need to examine whether advances in AI technologies "reshape how organizations develop and use complementary assets" (Berg, Raj & Seamans, 2023: 424). Currently, we only have limited insight into the nature of the complementary assets that allow organizations to take advantage of AI. Davenport, Hoerl, Kuonen, and Redman (2023), for example, stress the importance of creating data-driven cultures with a holistic vision, redesigned organizational structures, and new roles. Others highlight the importance of complementary human capital and supportive human resource management practices (Suseno et al., 2022). Given AI's potential to advance rapidly in terms of scope and sophistication (Berente et al., 2021), future research should not only identify which complementary assets are needed but also how organizations develop and renew them.

Second, when organizations deploy AI for isolated tasks, linkages to corporate or business strategies are often weak. Not surprisingly, the scholarly discussion about how AI changes strategies and business models (Gregory, Henfridsson, Kaganer & Kyriakou, 2021; Iansiti & Lakhani, 2020; Kemp, 2024) evolved independently from the literature on managing with AI. The chasm between these debates is problematic since an increasing number of organizations adopt AI visions and strategies (Davenport & Mittal, 2023a, 2023b). Future research should explore how managing with AI creates the capabilities for developing and implementing AI-based strategies. Moreover, scholars could also expand our understanding of how identifying and pursuing AI business cases provide the motivation, leadership support, and funding for scaling managing with AI initiatives and capabilities in organizations.

Third, there is conceptual research on task-level structures enabling HAIC (Choudhary et al., 2023; Puranam, 2021; Shrestha et al., 2019). Scholars should also analyze emerging organizational-level structures for managing with AI, such as the creation of venture capital units (Chalmers et al., 2021) or corporate centers of excellence (Joshi, Buche & Sadler, 2023). A related question is whether organizations benefit from centralized or decentralized approaches to managing with AI. Davenport recommends, in different studies, both a unified approach at the enterprise level (Davenport & Mittal, 2023b) and flexibility for "grassroots" AI initiatives (Barkin & Davenport, 2023). Joshi et al. (2023: 74) reconcile these positions by proposing a "federation of expertise" model combining a centralized basis of knowledge, systems, and processes with decentralized embedded capabilities. They also conclude that most companywide AI initiatives fail due to structural issues, which underlines the importance of further research into this domain.

Collective Agency

Prior HAIC and AM studies conceptualized individual agency or one type of human agency in relation to AI. Conversely, our review revealed that multiple different and interconnected actors are engaged with AI, which results in collective agency.

Scope and dynamics. Early AI applications in management often required extensive investment to train models for specific use cases (Agrawal et al., 2018: 50). Not surprisingly, agency in relation to AI was limited to an elite group of organizational members with the necessary domain expertise and data science skills (Schou & Nesheim, 2024). These constraints dissolve with the emergence of generative AI applications, which function as a "democratizing force" given their "accessible, conversational user interfaces and broad applicability across tasks and domains" (Krakowski, 2024: 7). Generative AI, such as ChatGPT, is available at a low cost and easy to use for humans without data science skills, enabling "a wider range of individuals and organizations to harness its potential" (Krakowski, 2024: 7). This development does not mean that all organizational members' agency with regard to AI is equal, but more members interact with AI and play a more active role in these interactions. Workers, who were often described as having little agency in terms of AI (see the AM literature, e.g., Möhlmann et al., 2021), now use generative AI applications actively to tackle more complex tasks (Roslansky, 2023). For example, call center employees freed from routine tasks (through AI) start interacting with generative AI to better understand customer problems and develop solutions for them (Edelman & Abraham, 2023).

Organizational process. We expect AI's increasing availability and use throughout organizations to promote *hybridization*, which refers to the formation of hybrid collectives comprising multiple human and AI members. Accordingly, Dennis, Lakhiwal, and Sachdeva (2023: 308) describe a gradual shift in the conceptualization of AI from a simple tool to "AI team members [who] may participate in collaborative settings." Bouschery, Blazevic, and Piller (2023: 147), for example, describe the "emergence of hybrid innovation teams" and suggest that generative AI, given its abilities and limitations, should not be considered "as a stand-alone technology, but rather as an actor in an innovation team" (Bouschery et al., 2023: 150). Conceptualizing AI as a hybrid team member becomes increasingly relevant with advanced AI systems tackling "complex problems [that] are often characterized by interactions between many humans and many algorithms" (Stelmaszak, Möhlmann & Sørensen, 2024: 15). As a consequence, hybridization elicits collective agency in human-AI relations (Dennis et al., 2023).

Future research. As an emergent phenomenon, hybridization suggests two major avenues for future research. First, scholars need to explore hybrid team roles and responsibilities. Bouschery et al. (2023: 149) suggest that "building and orchestrating […] hybrid teams and allocating tasks between humans and machines become a new managerial task." Humans and AI can take on different roles within hybrid teams. For example, AI team members can act as coaches (i.e., advising other team members), contributors (i.e., taking over tasks that human team members had previously done), and coordinators (i.e., assigning work to specific team members) (Piskorski & Joshi, 2023). Furthermore, human and AI team members could have competing or complementary roles, and AI team members could be hierarchically superior or inferior to their human colleagues (Heimans & Timms, 2024). These diverse possibilities require future research on role assignment to (Kolbjørnsrud, 2024) and complementarities between (Tang et al., 2022) human and AI team members, as well as their consequences for agency and power in organizations.

Second, there is a need for research on hybrid team processes. Bouschery et al. (2023: 150) expect that "including algorithms as team members may also change the way how humans interact with each other in a team." Relatedly, Dennis et al. (2023: 307) argue that "the entry of AI team members into traditionally human-driven roles could […] influence collaboration by disrupting […] interpersonal aspects of teamwork." Consequently, interpersonal processes are likely to differ between teams with AI members and those with only human members, which could affect team performance. Future research should explore the conditions under which AI team members improve or disrupt performance in collaborative settings. In hybrid teams, for example, appropriate forms of coordination, delegation, and feedback could improve the collaborative performance (Dennis et al., 2023).

Systemic Interaction

Prior HAIC and AM studies described local interactions situated in space and time. Our review revealed a more systemic interplay of different interactions across space and time.

Scope and dynamics. As a general-purpose technology (Rathje & Katila, 2021), AI is "likely to affect many parts of the organization simultaneously, enabling new interdependencies within and between units" (Beane & Leonardi, 2022: 4). This tendency increases with AI's integration into a growing number of systems. Solution providers have started integrating AI with human resource management, customer relationship management, product development, and supply chain management systems (SAP, 2023). Furthermore, AI's self-learning capability dissolves traditional boundaries between developers and users who collaborate to improve system performance (Waardenburg & Huysman, 2022). This integrative effect of AI has "the potential to cut across different parts of the organization and create new interdependencies among people, data, and resources that did not previously exist" (Beane & Leonardi, 2022: 4; see also Davenport, 2018; Leonardi & Neeley, 2022).

Organizational process. AI's integrative effect is likely to contribute to the development of "an ecosystem of interactions and relations with and across the multiple actors involved in [AI's] creation and deployment" (Anthony et al., 2023: 1673). This *systematization* of AI in organizations explains why AI applications in management increasingly occur in multi-agent settings that "involve complex interactions between humans and multiple […] algorithms" (Stelmaszak et al., 2024). The resulting systems of relationships include a wide range of interdependent actors, such as data scientists developing AI, managers and knowledge workers using AI, and workers generating data that feed and train the algorithm (Waardenburg & Huysman, 2022). Configuring these systems of relations is a dynamic process, and interactions between actors evolve over time (Anthony et al., 2023). Consequently, systemic interactions characterize managing with AI rather than isolated, local interactions.

Future research. The systematization of AI in organizations highlights two gaps in our understanding, requiring future research attention. First, scholars need to uncover the broader systems of relations between all the actors involved in AI's development and use (Anthony et al., 2023). This involves recognizing the multiple and often complex interactions between different human actors and AI. Scholars could, for example, move beyond dyadic relationships by exploring managers' and workers' interdependent interactions with an AI system (Leavitt, Barnes & Shapiro, 2024). This also suggests moving beyond human-AI interaction to also consider continued human-human interaction and emergent interaction between AI systems (Stelmaszak et al., 2024). For example, organizations use multiple algorithms to perform different managerial tasks in a coordinated way (Piskorski & Joshi, 2023; Shaikh & Vaast, 2023). While it makes sense to use a "focal point to start analyzing the system" (Anthony et al., 2023: 1686), such as zooming in on relations between workers and AI, it is equally important to consider these interactions' embeddedness in a broader relational system.

Second, future research should examine the evolutionary character of interactions around AI, rather than taking a "snapshot-in-time perspective" of isolated encounters between one algorithm and one human (Stelmaszak et al., 2024: 47; see also Anthony et al., 2023; Glaser, Pollock & D'Adderio, 2021). AM research, for example, showed that AI collects data on workers' changing behavior in real time (Newlands, 2021). HAIC research added the insight that AI algorithms use this emergent data to constantly learn and adapt their behaviors (Asatiani et al., 2021). Consequently, continuous system development characterizes managing with AI (Bailey & Barley, 2020; Waardenburg & Huysman, 2022). This continuous learning cycle is not limited to algorithms, as humans observing AI systems' adaptations can also learn and adapt their behaviors (Cameron & Rahman, 2022; Pachidi, Berends, Faraj

& Huysman, 2021). These insights suggest that it is difficult to comprehend human-AI interaction without a more dynamic conception of data flows, learning cycles, and behavioral adaptations.

Multilevel Outcomes

Prior HAIC and AM studies described specific, micro-level outcomes. Our integrative framework showed evidence that more diverse, and partly unintended, outcomes emerge across multiple levels, thereby affecting a variety of stakeholders and society at large.

Scope and dynamics. Managing with AI has effects that spread across organizations and society (Anthony et al., 2023). This outward impact of organizational AI applications could generate efficiencies and promote learning that benefit customers, partners, and even the broader economy or society (Brynjolfsson & McAfee, 2014). However, it could also cause ethical challenges and harmful behaviors associated with the use of AI in organizations (Christian, 2021; Floridi, 2023). AI's technological progress as a general-purpose technology increases this outward impact because more complex systems, such as generative AI, have "emergent abilities" that lead to unexpected outcomes (Wei et al., 2022: 1). Furthermore, AI applications' increasing scale and scope in organizational applications multiply AI's outward impact. For example, scholars describe AI's escalating energy and water consumption (Dhar, 2020; Kumar & Davenport, 2023) but also its increasing deployment to solve complex societal problems (Vinuesa et al., 2020).

Organizational process. We expect AI's outward impact to promote *societal integration*, which refers to the formalization of AI governance within and across organizations. Societal integration involves structured policies and frameworks that govern AI technologies' development, deployment, and oversight. These policies and frameworks are designed to ensure that AI systems operate ethically, transparently, and in alignment with societal values (Floridi, 2023). While early AI governance initiatives were informal, organizations increasingly establish formal AI ethical principles, review boards, and offices for responsible AI (Davenport & Bean, 2023; McElhaney, Smith, Rustagi & Groth, 2023). Multiple factors, including organizations' increasing willingness to accept moral responsibility (Floridi, 2023), growing public or consumer pressure (Yan, Chen, Zhou, Dai & Yang, 2024), and stronger regulatory oversight (Blackman & Vasiliu-Feltes, 2024) drive this tendency toward societal integration. However, research also shows that organizational members' vulnerability (e.g., due to their marginalized backgrounds) can put them at risk when attempting to drive their organizations toward more ethical practices (Ali, Christin, Smart & Katila, 2023).

Future research. Managing with AI's societal integration provides several avenues for future research. First, while HAIC and AM are vibrant research communities, they only have a peripheral position within the broader AI discourse (Anthony et al., 2023; Jain, Padmanabhan, Pavlou & Raghu, 2021). An organizational perspective on managing with AI could serve as a conceptual bridge connecting the micro-level examinations of HAIC and AM to the macro-level conversations, such as those pertaining to AI's impact on the labor market (Autor, 2015; Brynjolfsson & McAfee, 2014), to ethical concerns such as equality, privacy, and security (Floridi, 2014; O'Neil, 2016; Zuboff, 2019), and to the challenges associated with governing AI within the broader social system (Bostrom, 2014; Russell, 2019).

Second, we call for research on micro-macro linkages, such as studies examining how individuals' and organizations' deployment of AI in managerial tasks influences external actors, institutions, and societies at large. Macro-level research, for example, suggested that AI's opacity and emergence contribute to "accountability gaps" (Mittelstadt, Allo, Taddeo, Wachter & Floridi, 2016: 11) that allow organizations to refuse responsibility for AI's unintended societal effects. By linking micro- and macro-level research, scholars could advance our understanding of how managing with AI in organizations causes and escalates these accountability gaps, and how measures of societal integration could mitigate such harmful tendencies (see Grote, Parker & Crowston, 2024). Furthermore, studies outside our review sample show that individuals such as chess grandmasters' (Dahlke, 2023) and organizations such as accounting firms' (Goto, 2022) adoption of AI for decision-making has disrupted institutional arrangements and contributed to new occupational identities and routines in the global chess and accounting communities.

Third, external actors and institutions could, in turn, influence individuals' and organizations' managing with AI practices. Institutions provide regulative, normative, and cultural schemata influencing how individuals make sense of AI technologies (Scarbrough, Chen & Patriotta, 2024). Consequently, managing with AI practices within the same institutional setting could become more similar with increasing societal integration (Endacott & Leonardi, 2023), leading to subsystems within a global AI ecosystem dominated by few interconnected organizations and institutions (Jacobides, Brusoni & Candelon, 2021). Furthermore, interconnected institutional actors could construct boundaries around algorithms in a field to delimit their interactions with the environment (Marti, Lawrence & Steele, 2024). We call for studies that explore such macro-micro linkages to shed light on how new practices diffuse across organizations, converge or diverge within industries, and affect competition.

CONCLUSION

While disparate and partly opposing perspectives highlight specific aspects of reality, juxtaposing and integrating across perspectives help produce “more complete views of organizational phenomena” (Gioia & Pitre, 1990: 587). Following this wisdom, we developed an integrative framework that surfaces the linkages across the current HAIC and AM perspectives. By employing this integrative framework, we endeavored to develop a more encompassing organizational perspective on managing with AI. We envision future research on managing with AI spanning these multiple coexisting views and generating more complete knowledge than a single perspective could. The result is a vibrant field, replete with diverse perspectives that enrich our understanding of organizations’ increasing use of human-AI interaction for managerial tasks and its organizational and societal implications.

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