Editorial:

Capturing a Moving Target: Developing Research On and With AI for *Human Relations*

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Abstract

Artificial intelligence (AI) has become part and parcel of scientific knowledge production since the latest iterations of generative AI models (e.g., ChatGPT, DeepSeek, Claude, or Gemini) became widely available. Given AI has rapidly evolved since the initial release of ChatGPT in 2022, researching how AI's capabilities impact organizations and how researchers make use of AI tools can be likened to a moving target. In this editorial essay, we explore the implications of the introduction of AI in the context of academic research, both as the subject of investigation (i.e., research *on* AI) and as a research tool to facilitate academic writing, data generation, or the peer review process (i.e., research *with* AI). Specifically, concerning research *on* AI, we consider issues around clarity regarding both existing definitions and concepts in the AI literature and how these are influenced by the rapid technological evolution of AI's capabilities. In regard to research *with* AI, we reflect on the advantages and disadvantages of the use of AI as a research tool and discuss the *Human Relations AI Usage Policy*. Overall, our aim is not to be overly prescriptive on how to conduct research on and with AI but to encourage authors to reflect on how to best capture AI as a moving target in the context of their research endeavors.

Keywords: AI in organizations; research on AI, research with AI; *Human Relations*

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Introduction: AI research as a moving target

Generative artificial intelligence (henceforth AI) has become one of the most important topics for organizations in the 21st century, with some scholars and practitioners welcoming this development (Fountain et al., 2019; Fredberg & Schwarz, 2024; Hermann & Puntoni, 2024; Mudassir et al., 2024) and others being more skeptical (Bengio et al., 2024; De Cremer & Stollberger, 2022; Lindebaum & Fleming, 2024; Moser et al., 2022). Whether AI will turn out to be a boon or a bane for organizations and its members will also depend on the way jobs will either be automated or augmented as a result of AI implementation (Langer & Landers, 2021; Parker & Grote, 2020; Raisch & Krakowski, 2021), with organizations currently taking action one way or another. Given this backdrop, management and organization scholars are focusing their attention on AI as a burgeoning topic of inquiry (Bankins et al., 2024; Budhwar et al., 2023; Dwivedi et al., 2023; von Krogh, 2018; von Krogh et al., 2023).

Yet, the value of AI research for organizations and readers of *Human Relations* will only be truly realized if it is conducted in a way that allows for scholarly insights to accumulate into a coherent body of knowledge on AI in organizations. A popular metaphor for how knowledge accumulates in the social sciences is the notion of scholars partaking in a conversation (Kuhn, 1970). Accordingly, empirical research represents individual scholarly voices that are synthesized through reviews and meta-analyses, thus allowing knowledge to accumulate over time and scholarly conversations to emerge (Chan & Arvey, 2012; Ogbonnaya & Brown, 2023). In the past, these conversations took place between successive generations of human scholars, however, recently AI entered the conversation in organization studies as both 1) the subject of investigation (i.e., research *on* AI; e.g., Einola et al., 2024) as well as 2) a research tool facilitating academic work (i.e., research *wit*h AI; e.g., Gatrell et al., 2024).

Conversations about AI and research are noteworthy because AI represents a *moving target*; both the technology itself and the psychology of its use are evolving at a rapid pace, which has the potential to change scholarly conversations and influence the way scientific knowledge accumulates (Grimes et al., 2023; Grossmann et al., 2023). Indeed, because of its dynamic nature AI is not just considered a novel technology, but "a moving frontier of next-generation advancements in computing" (Berente et al., 2021, p. 1435). Given the increased prevalence of AI both in organizations and in organization studies, our goal with this editorial is to offer guidance for authors on what our editors and reviewers will consider when evaluating both research *on* AI (i.e., the study of AI concepts, such as AI ethics, AI leadership, AI creativity etc.) and research *with* AI (i.e., the use of AI in research practice). First, we will offer reflections on how the rapid pace of AI development impacts research *on* AI, including the importance of how AI is defined and how AI concepts evolve alongside the evolution of AI tools' capabilities. Second, we discuss the implications of research *with* AI, including the use of AI tools for academic writing, data generation, and in peer review. Finally, we offer some reflections on how to capture AI as a moving target, both in terms of research on and with AI, and conclude by discussing the *Human Relations* AI Usage Policy.

Research on AI

We start by considering research *on* AI, including reflections on the role of AI definitions and AI concepts as the bedrock of a coherent literature on AI in organizations.

AI definitions as a moving target

A first point to stress is that scholars have long emphasized the importance of clearly defining phenomena of interest as part of a joint academic discourse on a theoretical concept (Podsakoff et al., 2016; Suddaby, 2010; Wacker, 2004). Failure to clearly define a concept can lead to undesirable consequences that can adversely impact both study conduct as well as the interpretation of findings. For quantitative research, these can include the development of deficient measurement scales, measurement model misspecification, and the generation of weak theoretical rationales for hypotheses (Mackenzie, 2003). For qualitative research, a lack of definitional clarity can hamper the quality of qualitative concept analysis (Goertz & Mahoney, 2012; Podsakoff et al., 2016) as well as negatively affect participant recruitment, questions asked, methods used and, ultimately, research outcomes (Wynn, 2024).

In line with our aim to not be prescriptive, we do not seek to provide a conclusive AI definition here given relevant definitions differ depending on context and type of technology (e.g., AI chatbots or robots; Mariani et al., 2023; Yam et al., 2021). Instead, we intend to consider broader issues around the clarity of AI definitions and their implications for the AI literature. When looking at the state of definitional clarity (or lack thereof) in AI research, it becomes apparent that it is riddled with jingle (i.e., defining concepts differently when they are in fact the same) and jangle (i.e., using a common definition for different concepts) fallacies (Gonzalez et al., 2021; Kelley, 1927; Shaffer et al., 2016). The jingle fallacy of AI is aptly illustrated by a review of the AI literature commissioned by the European Union in 2021 that found no less than 59 different definitions of AI (Samoili et al., 2021). Although the authors highlight that the reviewed AI definitions share some commonalities, such as AI's ability to engage in sophisticated information processing, its capacity to make decisions with a high degree of autonomy as well as its capacity to achieve specific goals set by humans, there are also substantial differences among available definitions. Such variety in how a concept is defined makes it more difficult – even for experts – to understand what needs to be done to advance knowledge in a domain, such as AI in organizations (Solinger et al., 2024).

Similarly, the jangle fallacy in the AI literature relates to how the definitional umbrella of AI includes many different types of technology such as computer programs (e.g., Microsoft Excel Macros), algorithms (e.g., social media algorithms), robots (e.g., service robots in the hospitality industry), or generative AI chatbots (e.g., ChatGPT or DeepSeek). As an example, the European Commission's ethics guidelines for trustworthy AI list a variety of technologies under the umbrella term algorithmic decision-making systems that include algorithms, AI, and robots, among others (High-Level Expert Group on Artificial Intelligence, 2021). Forcing these very different forms of technology into alignment may lead to a neglect of phenomena relevant to the mission of *Human Relations*, such as differences in how humans interact and build relationships with different artificial technologies. For instance, research shows that when service robots make mistakes they are more easily forgiven by human collaborators because their embodied nature is more suitable for mimicking emotions and being perceived as human-like (Yam et al., 2021). The same, however, cannot be said of digital AI chatbots where service failure elicits negative affective reactions in human users, who also report a lesser ability of chatbots to "fake humanity" (Zhang et al., 2024).

Beyond these more obvious differences, recent research also showed that diverging definitions of AI entities can affect human perceptions of the respective system's properties (e.g., the complexity of an AI system) and their subsequent evaluation of these systems as more or less trustworthy (Langer et al., 2022). Definitional differences can, according to the authors, adversely impact the robustness and replicability of research, which is why subsuming different technologies under a generic AI umbrella term is not advisable. Informed by these examples, at *Human Relations* we regard it as essential that submissions adhere to our core principles of theory-method fit, that is, they should demonstrate internal consistency among elements of a research project, including definitions, research questions, research design, and theoretical contributions of AI research.

Taken together, the jingle-jangle fallacies of AI highlight a lack of definitional clarity in the AI literature, which complicates knowledge accumulation because study findings which have been derived from dissimilar concepts may be merged into one and the same evidence base (Shaffer et al., 2016). As a result, definitional clarity of AI as a concept needs to be increased (i.e., avoiding the jingle fallacy), while definitions of other, similar technologies, such as computer programs or robots, need to be rendered more saliently distinct (i.e., avoiding the jangle fallacy). This is especially important considering the pace of technological advancements in AI and related technologies, where the capabilities of some technological entities might evolve more quickly (e.g., generative AI; Mollick, 2022) than others (e.g., robots; Peel et al., 2024), rendering previous definitions of these entities partially (or fully) outdated.

All this begs the question of how two seemingly antithetical developments, that are, 1) the need for greater definitional clarity in AI research and 2) the rapid technological evolution of AI, can be reconciled. Recently, Solinger and colleagues (2024) pointed to a potential way forward by encouraging concept redefinitions (see also Astley & Zammuto, 1992) that promise to increase definitional clarity while also allowing for conceptual evolution. Specifically, the authors advance a typology of ten motives for concept redefinitions that they argue do not reflect cases of construct proliferation when the act of redefinition itself qualifies as a theoretical contribution. Applied to scholarship on AI in organizations, the redefinition type *stretching* (i.e., enlarging a concept's content domain) might be particularly valuable as it could be utilized to "update" and theoretically broaden the definitional scope of AI in line with successive technological advancements and associated evolutions in AI's capabilities.

AI concepts as a moving target

Podsakoff and colleagues (2016, p.3) define concepts as "cognitive symbols (or abstract terms) that specify the features, attributes, or characteristics of the phenomenon in the real or phenomenological world that they are meant to represent and that distinguish them from other related phenomena". Building on this, AI concepts can be thought of in terms of the various ways in which the introduction of AI in organizations influences how humans think, feel, and behave. Examples include AI trust (Glikson & Woolley, 2020), AI creativity (Jia et al., 2024), or AI coaching (Terblanche, 2024). However, similar to AI definitions, the utility of AI to automate, augment, or simply change work-related phenomena will also depend on the capabilities of the AI entity under investigation – capabilities that are constantly evolving.

To advance the scholarly discourse in Human Relations, it is crucial for research on AI concepts to not only extend scientific knowledge but also remain reproducible and reliable. However, given rapid technological advancements in AI and machine learning capabilities (e.g., Kapuscinski, 2024) paired with the slow pace of journal publishing (i.e., an average duration of 49 weeks assuming three rounds of revision; Huisman & Smits, 2017), there is a risk that research findings might be outdated shortly after they have been published. The resulting disjointed and incoherent evidence base also complicates knowledge accumulation in a domain, such as AI use in organizations, because it is more challenging to theoretically subsume what has been published under a broader sense-giving framework (Cronin et al., 2021a). For AI research findings to have greater longevity in the face of AI's evolving capabilities, we encourage authors to reflect on how their AI concept of interest might change over time from a *human perspective* (i.e., how changing human attitudes toward AI might change AI concepts). This is aligned with the mission of *Human Relations* to publish the highest quality research that advances our understanding of social relationships in and around work. More specifically, we encourage scholars to engage in prospective reflections to develop more future-oriented theories (see Gümüsay & Reinecke, 2024). When it comes to prospective reflections on AI's evolving capabilities, different approaches exist that can aid scholars to fine-tune their research questions, including 1) a consideration of future-of-work narratives or 2) taking a closer look at the technological basis of AI concepts.

The first approach encourages scholars to allow for their AI-related research questions to be informed by existing narratives in the public debate about what the future of work might look like. This is relevant because public narratives on a given subject, such as AI, have the power to influence organizational policies, shape organizational practice, ultimately leading to the more dominant narratives being adopted and "willed into being" (Levy & Spicer, 2013). The process by which narratives about the future of work shape what actually happens has recently been described by Dries and colleagues (2024). The authors distilled seven generic future-of-work narratives, such as AI augmentation of work or the need for re- and upskilling employees facing AI implementation in their organizations. These narratives are introduced by different actors in the public debate on AI, including economists, journalists, or policy makers, and have the potential to influence collective action (Dries et al., 2024). We suggest that by engaging with and indeed by challenging future-of-work narratives, scholars can prospectively reflect on their research questions on the AI concepts they study.

Reflecting on changes from a human perspective, scholars could consider which future-of-work narrative might apply to their AI concept of interest and whether they would envision said AI concept to change if the relevant narrative was adopted and turned into an organizational reality. For example, the narrative around AI augmentation of human work (Dries et al., 2024), which describes the necessity for AI and humans to collaborate on various work tasks is relevant for scholars studying AI creativity (i.e., the production of highly novel, yet appropriate, ideas, problem solutions, or other outputs by autonomous machines; Amabile, 2020) because it encourages reflections on how and when humans might work together with AI to produce creative outputs. This stands in contrast to earlier scholarly discussions on the potential of AI to augment human creativity, which suggested that humans would be disinclined to team up with AI in the context of creative work because creativity is strongly tied to intimate collaborative relationships among human co-creators (Huang et al., 2019; Rouse, 2020). However, human attitudes have evolved since then and recent research has demonstrated not just the possibility but the utility of humans working with AI to generate superior creative outputs (Doshi & Hauser, 2024; Jia et al., 2024; Lee & Chung, 2024).

In a similar vein, the future narrative around re- and upskilling employees prior to AI implementation (see Dries et al., 2024) is relevant for scholars researching concepts such as AI literacy (i.e., human proficiency in different subject areas of AI that enable purposeful, efficient, and ethical usage of AI technologies; Pinski & Benlian, 2024). Although efforts to increase AI literacy in organizations are crucial, imagining the possible implications of future changes in AI literacy rates through re- and upskilling programs in organizations as well as how changes in AI literacy might influence AI usage could be informative. Specifically, although initial research (Pinksi et al., 2023) indicated that increasing AI literacy promotes positive attitudes toward AI, more recent work showed that this is only the case for individuals with low AI literacy (Tully et al., 2025). Specifically, Tully and colleagues demonstrated that greater AI literacy decreases AI receptivity (i.e., openness to AI-based products and services) because users with greater AI literacy cease to have a sense of awe and magic when working with AI, thereby reducing the appeal of AI use altogether. Taken together, we suggest that prospective reflections from a human perspective on how future-of-work narratives might shape AI concepts of interest can support scholars by allowing them to fine-tune their research questions and "futureproofing" their research findings.

A second approach that can help scholars gauge the impact of AI's evolving capabilities on their research on AI is to take a closer look at the technological basis of AI concepts of interest. Although, contrary to engineering or computer science, social scientific research on AI has traditionally solely focused on the theoretical dimensions of AI concepts as opposed to their technological features (e.g., Matthews et al., 2025), we suggest that reflecting on how technology might influence theory is beneficial because AI concepts and AI's technological features are inextricably linked (see Giarmoleo et al., 2024 and Tsai et al., 2022 for a similar argumentation). We therefore encourage prospective reflections, as before, from the vantage point of a *human perspective* (i.e., how changing human attitudes toward AI might change AI concepts) on whether the technological basis of AI concepts is likely to rapidly evolve, and how the technological development of AI's capabilities informs human attitudes toward AI.

From a human perspective, perceptions of AI and its use are likely to evolve as well; typically, from being more resistant to change at first (Golgeci et al., 2025) to a more routinized everyday AI use (Weibel et al., 2023) as AI tools both become more common in the public discourse as well as more prevalent in organizations. The implementation of AI in society and organizations is likely to also have an impact on norms and behaviors similar to normative-behavioral changes in reaction to other major societal events, such as Covid-19 (Diekmann, 2022; Saxler et al., 2024), or prior technological innovations, such as the introduction of social media (Haidt, 2024; Haidt & Lukianoff, 2019). Therefore, in response to technological advances, changing human attitudes toward AI might also influence AI concepts, which is why we encourage AI scholars to consider whether an acclimatization to the introduction of AI into organizations and the associated normalization of the technology will affect AI concepts of interest. For example, the concept of AI leadership is currently undergoing a process of normalization in organizations that, thus far, involves the routinized reliance on algorithmic management in a gig work context (e.g., food delivery drivers or ride hailing platforms such as Uber; see Keegan & Meijerink, 2025 for a review) and in the near future might involve joint human-AI leadership replacing exclusively human leadership (Hillebrand et al., 2025) or leadership that involves human-robot collaboration (Tsai et al., 2022). Current research on AI leadership reflects human attitudes that are more in line with a romanticization of human leadership and a relative devaluation of any form of artificial leadership. For instance, when being led by AI tools, such as ChatGPT, followers view the leader as having lower status and the job tasks in question to have lower complexity (Jago et al., 2024). However, scholars predict that such reticence toward AI leadership will be short-lived and future AI tools will be embraced as leaders, and perhaps even preferred over their human counterparts (Quaquebeke & Gerpott, 2023). This is because AI leaders will be more able to satisfy human's basic psychological needs of autonomy (e.g., by more readily providing real-time information), competence (e.g., by offering more bespoke and motivational feedback), and relatedness (e.g., by being empathetic communicators).

Likewise, given that coaching is strongly related to the quality of human social skills, AI coaching (see Terblanche, 2024) represents an AI concept that is also subject to change in line with changing human attitudes. Arguably, human attitudes toward AI coaching will become more positive the more AI becomes anthropomorphized (i.e., its behavior is imbued with humanlike characteristics, motivations, intentions, and emotions; Epley et al., 2007) and is able to conduct human-like coaching interactions (Terblanche et al., 2022). For example, given the limited human-like appearance of early chatbots during coaching exchanges with clients, previous AI coaching research predicted AI tools to have a rather modest impact on coaching effectiveness (Graßmann & Schermuly, 2021; Weber et al., 2021); however, latest versions of ChatGPT can remember prior interaction content and analyze text for user preferences to make interactions more bespoke and pleasant (Fan et al., 2023; Matz et al., 2024). AI-powered robots can take this functionality even closer to mimicking real-life coaching interactions that may be comparable to those with human coaches in terms of their impact on coaching effectiveness (Spitale et al., 2023), making it more likely that human attitudes toward AI coaching will change over time. Taken together, scholars working on topics, such as AI leadership or AI coaching, are more likely to be affected by the technological evolution of AI capabilities as AI leaders and coaches are becoming more human-like and will be perceived as more effective. Extrapolating from this to submissions to *Human Relations*, our intention is not to invite submissions studying technological aspects of AI or indeed how successive versions of AI tools might influence organizational phenomena. Indeed, we would contend that publishing such research is within the purview of other outlets, such as those focusing on IT or computer science. Instead, in line with the mission of *Human Relations* our aim is to encourage scholars to prospectively reflect on the bespoke and contextualized implications of the rapid technological advancements in AI's capabilities for their AI concepts from a human perspective and, if warranted, to refine their research questions in consideration of future developments on AI use in organizations.

Conclusion: Research on AI

The rapid technological progress regarding AI's capabilities alongside the changes in how AI is implemented and used in organizations creates a dynamic environment for scholars where research on AI can seem like attempts at capturing a moving target. Speaking to this, we posit that there is a need to more accurately capture AI concepts of interest, which puts particular emphasis on definitional clarity as well as concept clarity, which is necessary for scholars to produce reliable evidence, build coherent literatures and theories, and ultimately shape the scientific conversation on AI moving forward. When it comes to describing different pathways toward scientific knowledge production, an informative distinction can be made between research that builds *unit theory* (i.e., specific models that are proposed and empirically tested; e.g., the specific impact of AI on human creativity) and research that is integrated as *programmatic theory* (i.e., general knowledge on a topic derived from the collection of verified unit theories; e.g., the general impact of AI in organizations; Cronin et al., 2021b, 2021a). Given that programmatic theories are built from and thus depend on the accuracy of unit theories, the concepts investigated by unit theories need to be clearly defined and rigorously tested. Applied to research on AI, this editorial can be understood as a call to build appropriate unit theories on AI, algorithms, robots, and other artificial technologies that would then enable the establishment of valid programmatic theories on AI in organizations.

Research with AI: AI use in research as a moving target

In the following, we will consider research *with* AI, that is, the proliferation of AI tools to facilitate scholarly work. Specifically, we discuss potential advantages and disadvantages of AI for academic writing, data generation, and its use in peer review. We conclude each section by stating our editorial position that is summarized in the *Human Relations AI Usage policy* (see the policy at the end of the editorial and on the Human Relations website).

AI as a tool for academic writing

In this editorial, we do not intend to offer an exhaustive list of existing AI research tools – partly because these tools are constantly evolving – but point interested readers to other work that offers such overviews (see e.g., Delios et al., 2024; Gatrell et al., 2024).

Independently of which tool is utilized, AI is increasingly used to brainstorm ideas, conduct literature reviews, as well as to edit and revise academic writing for submission to academic journals. The widespread introduction of AI as a research tool ignited a passionate discussion in the academic community where AI is embraced by some (Dergaa et al., 2023; Dwivedi et al., 2023; Grimes et al., 2023) but criticized by others (Bechky & Davis, 2025; Cornelissen et al., 2024; Larson et al., 2024). The purported advantages of AI for academic writing or, more generally, in the preparation of academic papers, lies in enhancing academic productivity and research efficiency by processing and synthesizing vast amounts of textual data, essentially synthesizing entire literatures in a speedy fashion (Dergaa et al., 2023). Indeed, scholars suggest that "GenAI appears to be capable of writing everything that has to be written up along all research process stages" (Delios et al., 2024, p. 8) from aiding idea initiation to facilitating the final write-up for submission. In a similar vein, Grimes and colleagues (2023) count greater efficiency in knowledge synthesis across diverse literatures, greater rigor in data collection and analysis, less bias in peer review, and support in translating research findings for organizational practice among the advantages of AI for academic work.

These rather positive responses to AI implementation in academic research are accompanied by more critical voices as well. Generally, these critical voices worry about how AI use influences scholars themselves and how AI's proneness to hallucinations could reduce the quality, credibility, and perhaps even the ethicality of human scholarship (see Kulkarni et al., 2024 for an overview). Specifically, Bechky and Davis (2025) caution that AI imperils the notions of craft and community as core features of academic work and call for scholars to resist the algorithmic management of science moving forward. Specifically, the authors suggest that craft implies doing scientific work well and "with our whole selves" (Bechky & Davis, 2025, p.11) by deeply engaging with literatures and in interactions with a community of academic and practitioner colleagues. They stress that if this craft would be outsourced to

AI, this may lower the quality of academic craftsmanship in the future. Similarly, Cornelissen and colleagues (2024) critically discuss the utility of AI tools for the purposes of theorizing and reflect on the consequences of automating or augmenting human theorizing. On the one hand, the authors conclude that AI cannot theorize by itself, implying that researchers aiming to automate their theorizing activities are ill-advised. And although AI-augmented theorizing is highlighted as an option, they caution that employing AI in this way will diminish the richness of theorizing to a more predictive and unitary approach. In their words, AI use will "limit the range of what we understand phenomena to be, and what in turn we can theoretically say about them, at the expense of what else we might otherwise theorize about organizations and organizational life. This would without a doubt constitute impoverished, certainly not enriched, scholarship" (Cornelissen et al., 2024). Finally, another group of scholars (Larson et al., 2024; Lindebaum et al., 2024; Lindebaum & Fleming, 2024) offer stark warnings of the impact of AI on the critical thinking abilities of management scholars, suggesting that AI use could undermine both objective decision-making and scholarly reflexivity in scientific enquiry, thereby harming responsible management research.

As a journal, *Human Relation*'s stance on the use of AI in academic writing is that it should be done in a responsible and transparent way. We do not prohibit authors from using AI tools to edit or proofread their scholarly work, however, the possible consequences of such augmentations – both positive (e.g., greater efficiency) and negative (e.g., inaccuracy of hallucinations) – are the responsibility of the submitting authors. Furthermore, as part of our *Human Relations AI usage policy*, we emphasize the requirement to transparently disclose any AI use, for instance, for the purpose of idea generation, literature searches, as well as for editing and proofing manuscripts, both in the cover letter as well as the methods section of submitted manuscripts. As editors, we also reserve the right to reject submitted manuscripts or retract published papers should it at any point be discovered that AI usage has not been fully and transparently acknowledged.

AI as a tool for data generation

In addition to utilizing AI to augment academic writing, there have been calls across the social sciences, for example in marketing (Sarstedt et al., 2024) or management (Wang et al., 2024) disciplines to make use of artificially created so-called silicon samples. Silicon samples refer to the creation of new samples of synthetic data based on real underlying data with the help of large language models. Wang et al. (2024; p.2) define synthetic data as "artificially generated data designed to emulate the original data as closely as possible without revealing actual observations in that data". The promised benefits of this method include an easier anonymization of raw data that could encourage easier data sharing in the interest of open science practices (Wang et al., 2024). Other, more optimistic arguments in favor of silicon samples include the notion that creating artificial samples from existing data is less costly than collecting primary data from human participants (Manning et al., 2024).

In contrast, a less charitable view on the implications of artificially created data in management research is its potential to supercharge AI-automated data fabrication on an unprecedented scale (Bechky & Davis, 2025). Whereas prior data fabrication attempts could be addressed by requiring authors to make data sets and syntax available for re-analysis (e.g., Aguinis et al., 2018), synthetic anonymization of source data might be exploited to obfuscate the origin of source data and thus lead to a more difficult-to-detect form of data fabrication because it circumvents the sharing of source data by design. Further complicating the utility of silicon samples, recent research (Shumailov et al., 2024; Xing et al., 2025) showed that synthetic data generation might not be a panacea in the way more optimistic accounts suggest. According to the authors, once silicon samples have been published and are publicly available, they will become available as training data sets for future AI models, which will at that point not only contain real, human-generated data but also the synthetic data. This is problematic because, over time, a real data vs. synthetic data tipping point will be reached in AI training data, meaning that subsequent AI models that are trained with, in part, synthetic data will be irreversibly damaged by such "polluted data", eventually causing what the authors call a "model collapse" that leads AI tools to "mis-perceive reality" (Shumailov et al., 2024, p. 755).

Because it is our view that the disadvantages of using AI as a tool for data generation outweigh its potential benefits, *Human Relations* will not accept any submissions that feature AI-generated datasets. Silicon samples created by AI are opaque, cannot be easily verified, and are fundamentally unsustainable given that the more synthetic data is produced the more likely it is for future AI models to collapse and produce inaccurate silicon samples.

AI as a tool for peer review

Given there are legitimate issues when it comes to the peer review process that are worthy of discussion, including a lack of qualified reviewers, subjectivity and bias of some reviews, or the potential for disagreement among reviewers (see Aczel et al., 2025 for an overview), some scholars are advocating for the use of AI as an assistant in the peer review process to augment the work of both reviewers and editors alike (Checco et al., 2021; Dwivedi et al., 2023; Sarker et al., 2024). For instance, some suggest that AI tools could assist authors in improving the quality of academic writing and depictions used in the manuscript, thereby reducing desk reject decisions of journals that might be influenced by the way the manuscript is presented (Checco et al., 2021). Others encourage the use of AI tools for editors to pre-screen papers for journal fit, serious logical or methodological issues, as well as to evaluate the quality of review reports received from peer reviewers (Sarker et al., 2024). The overall impression of AI advocates seems to be that the use of AI for peer review is comparable to that of existing writing assistants, such as Grammarly, which came with productivity benefits (Dwivedi et al., 2023).

However, some scholars also see the use of AI in peer review more critically and are concerned that tools, such as ChatGPT, could corrupt the peer review process (Chawla, 2024). According to the authors, this is due to AI's potential to hallucinate and produce inaccurate reports. Additionally, because AI-augmented peer review involves giving AI tools access to confidential, unpublished academic manuscripts, this could have copyright implications (see also Van Dis et al., 2023 for a similar argument). They also highlight that the use of AI in peer review is not a theoretical exercise anymore but is likely to be widespread. For instance, in a recent case study of peer review in AI conferences after the release of ChatGPT, up to 16.9% of submitted reviews have been found to be substantially modified by AI (Liang et al., 2024).

Based on the preceding argument, at *Human Relations* we take a less flexible approach when it comes to using AI as a tool for peer review. We ask existing and prospective reviewers to refrain from using AI tools for the purposes of peer review. Our stance is not just informed by the familiar issues around hallucinations or possible copyright implications of such conduct but also because it does not align with the spirit of responsibility, transparency, and fairness that we all share as reviewers and editors. Consequently, we also ask editors (including special issue editors) not to use AI tools when evaluating manuscripts, when crafting responses to authors, or in any other part of their editorial work for the journal.

Conclusion: Research with AI

Academic work and, by extension, the academic profession is changing rapidly because of the introduction of AI tools with exponentially improving capabilities. In response, we, as editors, reviewers, and readers of *Human Relations*, see it as our duty to carefully weigh the advantages and disadvantages of conducting research with AI to develop guidance on the use of AI within the journal. Because we value each author's unique voice, be it as a writer or a reviewer of manuscripts, we kindly invite authors to submit their best work. For us, this means that we do not prohibit the transparent use of AI to augment academic writing; however, we do not allow AI use for the purposes of data generation or in peer review.

Conclusion

Advancing scholarly conversations has become both easier and more challenging since the introduction of AI. On the one hand, we see an exciting opportunity to study organizational phenomena that are touched by AI – one might say "'tis the season for research *on* AI" and studies on the role of AI in organizations are certainly burgeoning. On the other hand, we also see a complex picture with respect to how research *with* AI might impact on the quality of academic work in the future and have devised the journal's policy with this in mind. On balance, we remain cautiously optimistic about the potential of AI in the context of academic research. In closing, given AI is a moving target, we regard this editorial as the start of a conversation on AI use within our *Human Relations* community and, as such, will continue to deliberate on what constitutes the most adequate and appropriate guidance on AI use moving forward.

Appendix: Human Relations AI policy

Human Relations AI Usage Policy

For Authors:

- Human Relations will not accept any papers utilizing AI-generated datasets.
- All AI usage (e.g., editing, proofing, idea generation, literature searches) must be accounted for in detail in the cover letter accompanying your manuscript.
- All AI usage (e.g., editing, proofing, idea generation, literature searches) must be described in the methods section of your manuscript.
- Should it at any point be discovered that AI usage has not been fully acknowledged this will constitute grounds for rejection of a submitted manuscript or retraction of a published manuscript.

For AEs/Reviewers:

- AI tools should not be used to conduct manuscript reviews. Uploading an MS into ChatGPT for this purpose will make it part of the public domain which may be flagged during subsequent plagiarism checks.

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