THE FUTURE OF RESEARCH IN AN ARTIFICIAL INTELLIGENCE-DRIVEN WORLD

Mukta Kulkarni

Saku Mantere

Eero Vaara

Elmira van den Broek

Stella Pachidi

Vern L. Glaser

Joel Gehman

Gianpiero Petriglieri

Dirk Lindebaum

Lindsey D. Cameron

Hatim A. Rahman

Gazi Islam

Michelle Greenwood

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Abstract

Current and future developments in artificial intelligence (AI) systems have the capacity to revolutionize the research process for better or worse. On the one hand, AI systems can serve as collaborators as they help streamline and conduct our research. On the other hand, such systems can also become our adversaries when they impoverish our ability to learn as theorists, or when they lead us astray through inaccurate, biased, or fake information. No matter which angle is considered, and whether we like it or not, AI systems are here to stay. In this curated discussion, we raise questions about human centrality and agency in the research process, and about the multiple philosophical and practical challenges we are facing now and ones we will face in the future.

Introduction

Mukta Kulkarni
Indian Institute of Management Bangalore

At the end of November 2022, the San Francisco–based firm OpenAI released an artificial intelligence chatbot called ChatGPT (Generative Pretrained Transformer). ChatGPT is a large language model that generates realistic and persuasive sentences by mimicking language patterns from pooled textual materials from the Internet (Stokel-Walker, 2023). It can produce essays, summarize literature, suggest research gaps, create draft outlines for a research paper, and run statistical analyses. This technology may eventually design experiments, write manuscripts, and conduct peer review (van Dis et al., 2023). ChatGPT is but one example of an AI system. While AI-generated texts are not new—one Professor has used patented algorithms to generate about a million books since about 2006 (Podolny, 2015)—the likes of ChatGPT have become recipients of mass curiosity.

Despite regulations, restrictions, and bans across the world (Browne, 2023), these and forthcoming developments have the capacity to revolutionize the research process. On the one hand, through human-AI authorial collaboration, we may be able to pool resources, generate novel ideas by leaping across literatures, conduct analyses, and co-author manuscripts at extraordinary speeds. In fact, as of this writing in early 2023, at least four articles in medicine research have listed ChatGPT as a co-author (Stokel-Walker, 2023), and books are being produced in mere hours with a few prompts fed into ChatGPT, with the likes of Amazon listing over 200 books that list ChatGPT as an author or as a co-author (Bensinger, 2023). Researchers are also actively experimenting with such AI across the research process (e.g., as research assistants who ideate and run analyses, Korinek, 2023; as experimental subjects, Horton, 2023).

On the other hand, this human-AI authorial collaboration has not been without problems. While AI-generated content sounds authoritative, it is known for factual errors and misrepresentations (van Dis et al., 2023) to the extent that, in rare cases, the AI is seen as suffering "hallucinations" wherein its output does not correspond to any real-world records (e.g., referencing research papers that do not exist, providing unique identifiers of unrelated research papers, Alkaissi & McFarlane, 2023). Not only does such content affect the credibility of the human authors' research work, but it can also trick human reviewers who, in recent studies, were unable to spot AI-generated abstracts (Thorp, 2023).

Importantly, with regard to research output, this human-AI authorial collaboration problematizes our deeply held notion of authors as creators of "original work", a key parameter in most journals'—including *Journal of Management Inquiry's*—submission process. Publishers and research ethics officers believe that AI can be acknowledged to some extent in certain sections of the paper, but it is not an author as it cannot assume responsibility for the originality, consistency, and integrity of content, nor does it have the capacity to acquiesce to being an author (Stokel-Walker, 2023). But what if the output of the AI is original, credible, and attributable? Then would AI be an accepted author in our world of management and organization studies?

I asked ChatGPT if it considered itself an author. It responded that it did "not have the conscious intention or creativity of an author" but that "the text I generate could be considered authored by me, in a technological sense." It also told me that "AI language models like myself may be listed as co-authors if we have made a substantial contribution to the research process." It also gave me a verifiable and credible history of the word "author", noting that the notion of the author as a solitary, creative, original, and intellectual property right holder of the created work is a relatively recent one in the history of writing. This notion was developed and concretized during the Renaissance and the Enlightenment periods.

Key texts on authoring corroborate ChatGPT's answers. Indeed, as late as the 1750s, someone who wrote was one of the many craftspersons involved in the production of a book, and not the most important one. This collaborative aspect of producing texts was also seen from the Middle Ages through the Renaissance wherein valued and authoritative texts derived, and not deviated from, prior texts as creators often complied, commented upon, and authored work by building on other's ideas (Woodmansee, 1992). In some cases (e.g., for folk tales and epics) it may not matter if there is an author for us to consider the texts authentic. In other cases (e.g., scientific reports on medicine) it might. In yet other cases (e.g., poems) the author can be seen as a product of the reader's interpretation of the text (Barthes, 1977). Viewed through the lenses of how we treat collaborations, types of texts, and the reader's roles in interpreting the output, the author is a social construct shaped by extant historical, economic, cultural, and legal forces (Woodmansee, 1994). As such, macro institutional systems lead to subjective positions that authors occupy, and the author need not always be someone who precedes a text and stands outside of it (Foucault, 1969). In an increasingly AI-driven world, the author as we know them today (an individual with agency and legal rights) may be seen as nothing but "a brief episode in the history of writing" (Woodmansee, 1992) whose "death" was imminent (Barthes, 1977).

Our questions about the social significance of an author and their authorship have assumed especial importance as we march in the direction of algorithm-driven authorship. We may not see the author as an intention-driven agent, and we may rethink our contemporary binary beliefs about someone being an author or not. Maybe we will consider AI-driven ventriloquism as authorship. As this is happening, as academics, we may have to overhaul our regimes of attribution, copyrights, and author valorization.

Depending on our treatment of AI in the research process, we might be at the precipice of a sea change in the channels (e.g., journals, books) through which the authors' contributions are curated and consumed. We might usher in an era of paper mills, or a Wikipedia style of authoring. Maybe our notions of a 'top tier' journal will involve showcasing how well human authors can collaborate with AI.

As Foucault (1969) has presciently noted, we might have to skip questions such as "Who is the real author?" and "'Have we proof of his authenticity and originality?" and instead ask, "What are the modes of existence of this discourse?", "Where does it come from; how is it circulated; who controls it?" Instead of worrying about the death, disappearance, or irrelevance of the human author, we may have to rethink our centrality in the research process as we consider AI as our enemy or collaborator. As AI proliferation subverts our contemporary beliefs concerning the primacy of human authors, of individuality, and of the author's voice as their identity, we are likely to encounter multiple philosophical and practical challenges in what we now understand as the research process, indeed the very institution of research.

In this curated discussion, Saku Mantere and Eero Vaara begin by noting that AI systems will problematize the narrative work of developing theories, as they write for and alongside us. While they highlight concerns (e.g., of authorship), they conclude that AI systems will enable us to develop novel theoretical discourses. Elmira van den Broek adds to this line of thought by arguing for human-AI hybrid forms of work wherein AI systems can help us (e.g., by challenging our assumptions) just as we refine and supplement them with relationally generated knowledge. Adopting a performative perspective, Stella Pachidi views AI systems as co-constituted with social actors, emphasizes humans' lived experiences in the research process, and notes that AI is set to shape knowledge production and scholarship. Vern Glaser and Joel Gehman take a step further and outline how AI can contribute to research (e.g., as an assistant) as guided by governance principles (e.g., verification checks).

Here is where we part company. Gianpiero Petriglieri refers to the human author's identity, their meaning-making, and chooses not to engage with an AI system that may be efficient and able but is not 'him' and not inspiring. Along similar lines, Dirk Lindebaum argues that ChatGPT undermines 'learning' to theorize, homogenizes theory, and distorts competition for the best ideas in management research. Lindsey Cameron and Hatim Rahman further caution us regarding the unintended effects of using AI systems as we approach data (e.g., the notion of a 'surprise' to an AI system may hinge on word frequencies in a text, which is quite unlike a researcher's emergent and iterative collection and analysis process which yields novelty). Gazi Islam and Michelle Greenwood conclude by drawing our attention to questions about moral agency (e.g., the specification of the sources of agency as we evaluate co-produced inattributable output).

How will AI change the narratives we write?

Saku Mantere and Eero Vaara
McGill University and University of Oxford

Theory building in management and organization studies (MOS) is a narrative exercise (Czarniawska, 1999; Locke & Golden-Biddle, 1997; Vaara et al., 2016). The theoretical contributions we make are not so much based on filling objectively discoverable "gaps in the body of knowledge" but rather narrative constructions in an evolving, intertextual discourse. Theoretical contributions are accomplished by reconstructing existing literature and adding to prior narratives by establishing or refuting coherence in a recreated narrative. This is demonstrated perhaps most clearly by the fact that there are no objectively discernible logical structures underpinning any of our known theories; individual theories are constructions of organizational phenomena that fall within the scope of ongoing research programs in the field (Ketokivi et al., 2017; Leone et al., 2021). Knowledge does not accumulate across the entire discipline, but rather research programs pursue questions within their defined scope and knowledge advances as a discourse around such questions, mainly within research programs (Ketokivi et al., 2017).

We are experiencing a very special point in time where advances in Generative Artificial Intelligence (AI) should make us pause and think about the implications for our scholarship in general and the narrative work in theory development in particular. This is because we are seeing the first generation of "artificial narrators" emerge; technologies that – tasked with topical and genre specifications – are capable of producing text in a seemingly autonomous fashion. This raises the question: To which extent will AI replace MOS theorists, and how will the work of theory development be impacted by it?

Tools such as ChatGPT, Bard and the like can be seen as innovations in a long trajectory of technological breakthroughs, tracing back to the very inventions that consolidated written language as a communications medium and knowledge repository. AI tools will most likely offer theorists the potential to be more effective and offer us new ways to construct our literature reviews, to analyze our empirical material, and to narrate contributions. This will transform some of our practices – undoubtedly helping in many ways, in particular those who have struggled with writing, or who are not native speakers.

The argument that technology will replace human tedium and liberate human creativity has proven to be problematic even before the advent of AI, however. The advance of technology, rather than liberating the world population to expand their horizons, has locked human labor into a technological matrix, which is evident in the fact that despite the momentous productivity gains due to technology in the 20th century, the average workday has not shortened (Frey, 2019; Suzman, 2020). Each new generation of technology fashions humanity into its own image; this expands horizons but also narrows them (McLuhan, 1964).

How all this will change the narratives we write as MOS scholars, interfaced with such new tools that write for and with us? This is a fundamental issue because with the advent of the large language models, it is beginning to look certain that AI will contribute to the work of synthesizing knowledge that exists in textual forms.

We foresee that at least four issues will become relevant during the next few years of theorizing: authorship, novelty of theories, power and ideology, and future genres of management research.

Authorship in the Age of Artificial Narrators

One of the key issues is how AI will impact our authorship as MOS theorists. Imagine that not far in the future, your word processor will start suggesting what to write next; this should not be too hard to conceive because your phone probably does this for text messages. But how about if, based on what you have written already, the AI will suggest the next paragraph? Or, maybe, upon seeing what you choose as a title, it will generate an entire draft text? Even better, maybe you can write an abstract and it will extend it into an entire paper to edit? Will there be a point when you will no longer edit but it will be enough to input parameters such as genre, style, length and so on, and AI will narrate what you need without little need of editing? Now, who wrote such a text? This challenges us to ask at which point will the question of authorship become antiquated, and scholarly communities will focus on ideas rather than whose ideas they are.

Novelty of Theories

In addition to veering clear off sensitive topics, machine narration also poses questions pertaining to novelty. How much of future knowledge production will be reproduction of existing information “validated” by AI? As AI works by generalizing across existing bases of human knowledge, will this lead into a myopic development where radically new ideas fail to emerge? This is not a trivial concern as the current versions of AI operate based on algorithms that use existing texts as a point of departure. Thus, although AI can also generate new knowledge, there is a genuine risk that the knowledge produced will be more a reiteration of accepted wisdom rather than genuinely new ideas or novel insights as findings become less and less disruptive over time (Park, Leahey, & Funk 2023). This is also linked with the language itself; if we reproduce the concepts and vocabularies in use, it becomes increasingly difficult to engage in critical thinking problematizing these very discourses.

Power and Ideology

Noam Chomsky recently (2023) called ChatGPT as “the banality of evil [---]” which “summarizes the standard arguments in the literature by a kind of super-autocomplete, refuses to take a stand on anything, pleads not merely ignorance but lack of intelligence and ultimately offers a “just following orders” defense, shifting responsibility to its creators.” Indeed, a conversation around heated or morally-laden topics with AI tends to create a sense of conversing with a corporate lawyer, trying to manage risk of the company being sued or dragged into scandal.

ChatGPT's voice is essentially a corporate voice that is governed by, rather than democratically chosen values, principles of mitigating corporate risk. If such tools become prevalent in social and human sciences, the new role of AI raises issues about critical thinking and writing. AI itself has no consciousness and is not capable of self-reflection, which is the basic requirement for challenging traditional norms and beliefs that silently oppress those incapable of promoting their own interests (Habermas, 1971/1967). But its rise will also impact our ability as human theorists to engage in critical reflection in conditions "governed" by all powerful machine learning algorithms with internal logics that are almost impossible to understand. Will this be a new form of Foucauldian (1980) system of power that is invisible and limit our discourse and narrative forms?

Future Genres of Management Theories

All this will also have an impact on the narrative types and genres. We may well see a radical reimagining in the prevalent genres of MOS theorizing. Digital publishing has changed surprisingly little when it comes to the *Introduction-Method-Findings-Discussion* article format we currently use, modelled on reporting findings in natural science. The pdf article is a successor of scientific annals that were published in print form and disseminated by mail.

It is also possible, however, that if AI will change the way we produce theory, it will also revolutionize the way we consume it. If AI will do reading for us, what happens to the practice of reviewing literature? If scholars do less reviewing of literature, will this also mean they will read radically less? What, specifically, will we be reading when reading theory? What will we conceive of as literature in the future? Will the ease of inputting genre parameters into AI help multiple genres proliferate, or will MOS scholarship become an a-theoretical field where data sets are shared and theories are reduced to empirical generalizations to serve prescriptions to managers?

In Conclusion

This text has been rich in questions and poorer in answers. We would like to think, however, that despite the seemingly exhausting pace of development in AI technology, scholars will be able to use such advances to develop more novel, more diverse and more authentic theoretical discourse, but this requires critical thinking not only about what we write but also how we do that.

Towards Hybrid Forms of Research:
How Large Language Models Reshape Knowledge Work

Elmira van den Broek
Stockholm School of Economics

In today's AI age, our scholarly community finds itself at the forefront of a transformative period as we prepare for the impact of large language models (LLMs) and other generative AI tools on knowledge work. Knowledge work, once the realm of people who "think for a living" (Davenport, 2005; Drucker, 1954), is becoming increasingly disrupted as tools like ChatGPT, Bing AI, and Bard enter creative activities that were once reserved for human experts. People have heatedly debated whether LLMs will enrich knowledge creation or radically disrupt it to the extent of causing widespread unemployment among workers whose job security was founded on their expertise (Agrawal et al., 2022; Rotman, 2023). Drawing on insights from practice-based studies on AI and knowledge work, I posit that these debates are rooted in a distorted image of what knowledge work entails in practice. Instead, I want to shift attention toward the role LLMs can play in triggering reflection on and adaptation of work practices, resulting in new human-AI hybrid forms of research.

LLMs refer to a class of AI systems that generate texts across various topics and domains, including scholarly work, by predicting the likelihood of a sequence of words after training on a large corpus of text (Susarla et al., 2023). In this sense, they differ from other AI-powered language tools like Grammarly or auto-correct in Microsoft Word by focusing on creating rather than improving content. LLMs also distinguish themselves from predictive AI systems used by management and organization scholars to build and test theories (von Krogh et al., 2023), by not only extracting patterns from data but also using these patterns to create "new" data. These systems are increasingly integrated in everyday software products, accompanied by grand claims of easing and speeding up the process of knowledge creation, assessment, and consumption. For instance, Microsoft 365 Copilot promises to "turn your words into the most powerful productivity tool on the planet" by integrating LLMs into apps like Word, PowerPoint, and Outlook (Spataro, 2023). Similarly, the qualitative data analysis software program ATLAS.ti is said to offer a "personal research assistant" by harnessing LLMs to automatically code your data (ATLAS.ti, 2023).

In light of these grand promises, it is critical to realize that many of the claims surrounding LLMs are grounded in a particular view of what knowledge work entails. According to this conventional perspective, knowledge is treated as an abstract entity that can be separated from its context and derived from the algorithmic processing of large datasets. As articulated by Domingos (2015: 9) in his book *The Master Algorithm*, "[AI systems] eat up information, digest it, and turn it into knowledge." However, practice-based studies teach us that knowledge has important relational elements that cannot be captured in probabilistic and stochastic models. These studies highlight that knowledge creation involves an active process of meaning construction, wherein people create, assess, and apply knowledge within social contexts and through interactions with others (Cook & Brown, 1999; Orlikowski, 2002; Pakarinen & Huising, 2023). In the case of AI development, for instance, statistical relationships discovered by algorithms are not "inherently meaningful" but require AI developers and domain experts to interpret and align them in relation to the broader vision and values within the organization (Van den Broek et al., 2021).

Shifting attention from knowledge as extractable by algorithms to knowledge as relational helps to understand why LLMs used to perform research work without close supervision of experts can produce outputs that are irrelevant, misguided, or even harmful. By presenting the most likely answer based on training on a large corpus of primarily internet data, LLMs can generate outcomes that do not necessarily resonate with people's actual needs, meanings, and interests. For instance, when using ATLAS.ti's AI coding feature to analyze a set of interview transcripts and fieldnotes, it generated an overwhelming amount of codes, most of which were highly generic and detached from the practice-based lens and theoretical concepts that guided my study. These findings may not come as a surprise, given that auto-coding features basically represent quantitative coding of qualitative datasets, and carry the danger of confusing different research paradigms (Kelle, 1997). It is thus crucial to realize that LLMs can overlook important nuances between research traditions, where the standards, methods, and patterns well-represented in the training dataset may take precedence (Susarla et al., 2023).

A more fruitful avenue, therefore, lies in the possibility of human-AI hybrid forms of research, where scholars critically reflect on and combine AI outputs with relationally generated knowledge. I found that these hybrid constellations can emerge as AI systems present experts with surprising patterns and solutions that challenge their existing assumptions, triggering them to reflect on and adapt their dominant practices (Van den Broek et al., 2021). Likewise, LLMs can expose researchers to alternative templates, patterns, and solutions that can lead them to modify existing activities. An interesting example is the use of an AI chatbot to anticipate potential audience responses to research ideas. By prompting the tool to simulate fictional editors from a leading journal to debate a manuscript at an early stage, one can explore possible misunderstandings and discrepancies regarding the study. Although AI's responses remain constrained to common linguistic forms observed in the dataset (Bender et al., 2021), they can assist in refining contributions by contrasting them with "known" questions, variables, and findings within a given scholarly community. As a result, hybrid practices of writing, brainstorming, and theorizing may emerge, as researchers engage with patterns found in the established corpus of text to sharpen their ideas and questions.

It is important to realize that these hybrid constellations do not arise magically: they require the deep and critical involvement of scholars given the probabilistic and stochastic nature of LLMs. LLMs are found to be highly persuasive by generating text that sounds intelligent (Van Dis et al., 2023), which may lead people to blindly accept or incorporate AI outputs. As discussed, solely relying on these outputs is likely to offer little enhanced value for scholars as LLMs are detached from the particular debates, questions, and standards that are important within specific research communities. LLMs, similar to other complex epistemic technologies, therefore require reflection, validation, and refinement from experts based on relationally generated knowledge within their respective fields (Anthony, 2018; Lebovitz et al., 2022; Pakarinen & Huising, 2023; Van den Broek et al., 2021).

To meaningfully engage with LLMs, management and organization scholars need to have the necessary expertise to judge the quality of AI outputs in relation to their intended activities. This entails, for instance, assessing whether AI's auto-generated codes align with theoretical concepts or if simulated "editors" present relevant arguments in light of recent scholarly debates. The crucial role of experts' knowledge in validating AI outputs has been recognized by previous practice-based studies on predictive AI systems (Lebovitz et al., 2022; Van den Broek et al., 2021), and is likely as important today. In this sense, researchers may find themselves in troubled waters when using LLMs for unfamiliar areas where they lack a foundational understanding to assess the relevance and usefulness of AI outputs for the specific activity at hand, such as using LLMs to summarize literature on a novel topic.

Scholars also need to prepare for investing ongoing effort in refining LLMs' behavior based on relational knowledge. One way of doing so entails prompt engineering, which involves adjusting the written instructions that guide the model's behavior. For instance, when using AI to anticipate reviewer responses, one can adjust the original prompt by explicating the reviewer's area of expertise or by employing intermediary outputs such as previous feedback. One can also "fine-tune" LLMs by training their foundation models on specific datasets that are closely related to the desired domain or research activity. For example, Susarla et al. (2023) suggest developing customized solutions for particular research communities by updating foundation models using data from published papers and submitted manuscripts. This shows the importance for scholars to engage in training and tuning LLMs in collaboration with AI developers to embed specific domain expertise. However, it is critical to realize that relational considerations that cannot easily be explicated and represented in digital data pose a limit to refining LLMs. In such cases, scholars will need to actively synthesize AI outputs with their own expertise or reflectively overrule them.

Ultimately, management and organization research, like other domains of knowledge work, stands at the beginning of a transformative journey with the uptake of LLMs. Although LLMs fall short of mimicking complex research practices, they hold the potential to generate novel hybrid approaches where AI systems become intricately intertwined with the ways through which research is performed. This calls for a continuous and iterative endeavor where researchers must develop new practices of reflection, validation, and refinement in relation to LLMs (Lebovitz et al., 2022; Krakowski et al., 2023), thereby blurring the boundaries between the design and use of AI systems (Van den Broek et al., 2021; Waardenburg & Huysman, 2022). Only then can we pave the way for a meaningful collaboration between humans and AI in the realm of research.

Large Language Models and the production of knowledge about organizations and management: Taking a performative perspective

Stella Pachidi

University of Cambridge

The emergence of generative artificial intelligence (AI) tools, that are capable of generating new content in the form of text, images or other media in response to prompts, has triggered significant fuss, reflections and contestations across various fields and disciplines. The production of knowledge is assumed to be deeply affected. Large Language Models (LLMs) in particular, are currently seen by many as the most remarkable breakthrough in AI research, with the newest versions such as GPT-4 showing "sparks" of Artificial General Intelligence, due to their ability to demonstrate broad capabilities of intelligence (Bubeck et al., 2023). LLMs include neural network models that are trained on massive sets of textual data and generate content in response to prompts by predicting the next word in a partial sentence. Despite their limitations to date such as limited input, outdated training data, embedded biases and hallucination models (Lightman et al., 2023), such tools are here to stay. Given that a big part of academic knowledge is codified into words, there is a legitimate concern about how the incorporation of LLM-based tools in our research practices may shape how we produce and share knowledge. In the following paragraphs, I will take a performativity lens to understand the impact of LLM-based tools on academic knowledge production in the field of management and organizations.

A Performative Perspective on LLMs. It is almost impossible to not think of performativity when considering the use of generative AI tools based on LLMs in organization and management research. According to Austin (1975), words do not only represent social reality, but they may also shape it. Organization and management theories are not only often developed through the analysis of language data, but essentially, they are highly shaped by the language chosen and written by organizational scholars, having performative effects in shaping how we understand and theorize (Gond et al., 2015), or even how managers and organizations act (Cabantous & Gond, 2011). Essentially, then, and unavoidably, the incorporation of generative AI tools such as those based on LLMs in our research process, as I will explain below, would have performative effects on how we make sense of and talk about organizations, how we develop our theories, and by consequence in what ways we impact managers and how they manage and lead their firms.

A performative perspective is highly useful to understand the use and impact of algorithmic technologies such as those based on LLMs (Glaser et al., 2021; Orlikowski & Scott, 2014). From a performative perspective, algorithms are not understood as independent entities, but they instead need to be considered as co-constituted with the social and material actors involved in the design, implementation and use (Orlikowski & Scott, 2008). Therefore, to understand how the use of LLM-based tools may affect the research process we need to take into consideration not only the idiosyncratic ways in which the researcher uses the LLMs as tools; or the perspective of the developers of the models; but also the practices and processes through which those models get trained; the contextual, situated practices through which the training data gets generated, captured and pre-processed; as well as the perspective of the actors involved in the training or the fine-tuning phases, and those providing feedback for reinforcement learning. Thus, the impact of such tools on our research process is shaped by “the emergent and constantly challenged outcomes of multiple different and partially overlapping performations” (Glaser et al., 2021; p.12).

Using LLMs for Data Collection. In the data collection phase, generative AI tools, especially those based on LLMs, can assist organizational and management scholars in a wide range of tasks (Susarla et al., 2023). Tools like ChatGPT could be used for example to extract data from archival sources such as identifying company information in an automated way given the variables identified by the researcher. Similarly, LLM-based tools could be used to pre-process interactions taking place via e-mail, forum discussions, social media and other web sources, and thus enable researchers to quickly collect data they would traditionally be drowning in. In the cases where the researchers know what exactly they are looking for and accordingly instruct the LLM-based tools through carefully constructed prompts, the tools could deliver such data extraction with high accuracy. The tools can also be seen as time-saving and insightful in more exploratory cases of research as well, where the researchers are likely to be agnostic and curious to identify interesting patterns and topics (Hannigan et al., 2019).

It is, however, important to note that generative AI is likely to lack the sociocultural context in which reports were produced, or in which interactions took place and views were shared. Its results would need to be carefully considered by the researcher who still needs to develop an essential affinity with the history, culture and structure of the research context. Furthermore, despite the ease with which the researcher may engage in extensive prompt engineering with an LLM-based tool in terms of what kind of data they are searching for in the available text, the model unavoidably contributes to making “agential cuts”, affecting essentially what world the researcher views and how they make sense of it (Barad, 2003; Orlikowski & Scott, 2014). This is because of the largely invisible workings of a model, and mainly the ways in which it is pre-trained and fine-tuned with billions of texts by other actors, which shape how the LLM may render topics, variables, and sentiments visible. Thus, generative AI tools come with performative implications for how an ontological orientation is shaped in the research process.

Using LLMs for Qualitative Data Analysis. Similarly, and perhaps even more consequentially, the use of generative AI tools would have performative effects on the data analysis phase of the research process. I was intrigued when Atlas.ti announced the integration of AI functionality into the latest version of their qualitative data analysis software, claiming to reduce data analysis time by up to 90% (Atlas.ti 2023). It is not difficult to get lured by this when faced with time pressures. LLM-based tools could anyway be useful as new, creative ways to look at one's data more creatively and look for unexpected patterns. They could prove handy when feeling 'stuck' and hoping to discover something new in your dataset. Of course, at the moment, the efficacy of the specific functionality is rather limited. However, given the scalability of generative AI development (OpenAI, 2023), I can easily see LLM-based tools being capable of processing large sets of text documents such as interview transcriptions and fieldnotes to extract codes and search for patterns.

But then again, such a tool cannot replace the situated, embodied interpretation of the organizational scholar who has lived experience from the field; who has developed a tacit understanding of the practices, the culture and the views of the informants; and who interprets the data, informed (often quite tacitly) by existing theoretical lenses. LLM-based tools are good at processing language and predicting the next token -whether that is a word following a sequence of words, or a sentence or even paragraphs. Let us not be fooled by the fact that ChatGPT could write a piece of text following the style of writing of a well-known writer, poet, or even a philosopher or sociologist. The fact that it can emulate a writing style is totally irrelevant to the ability to view the world, make judgments or reason as that person would. Thus, interpreting the insights and patterns identified by AI tools will need to be done with a heightened level of caution and questioning, and will likely require extensive prompt engineering by the researcher to guide the tool accordingly. One way or another, we are not merely looking at an augmented interpretation process, but at a collectively-informed process, if we take into consideration the interpretations, judgments, views and even biases imbued in the training datasets (Bender et al., 2021).

That said, an emergent capability of generative AI concerns in-context learning, which allows a user to adjust a model for a new use case without needing to perform extensive fine-tuning, but instead by providing it with examples through prompts (Xie & Min, 2022). This means that in the not-so-distant future, we may be able to train a model to search for quotes in our data that are similar to a quote we have already identified. While I am concerned about relying on generative AI for coding due to its performative impact, there could be great value and time saving when using it for triangulating our data across multiple sources.

Using LLMs for Writing. Let us not forget that LLMs are really good at processing language. They already are quite helpful in formatting the text in accordance with a specific style, proofreading, and reviewing for clarity and organization (Susarla et al., 2023). They do, however, and will continue to, require caution and careful and extensive interaction through prompts when it comes to having a generative AI tool to produce text, whether that is to help produce a clear abstract, create a summarizing table, or quickly generate a draft memo. As I mentioned at the start of this essay: Words matter; words have a performative impact. Our theoretical frames and situated, embodied context-informed interpretations tacitly shape how we codify our ideas through language. Even though knowledge is codified through academic papers, there is so much more that is gained socially through interaction and practice. Even if a generative AI tool can emulate the academic output, it cannot even closely act in the place of the tacit-knowing academic expert.

Besides, relying too much on an LLM-based tool could lead to path dependencies (Pachidi & Huysman, 2017). It is highly likely that in the future a LLM could be trained specifically from a scholar's personal style of writing. However, we as scholars develop over time and change our world views. Relying too much on a LLM could make us path-dependent and may constrain the natural, creative evolution of our writing style as we evolve. We will need to be particularly reflective on our own learning process, at times consciously distantiate ourselves from the LLM-based tool, and regularly prompt it in ways that may help accommodate the unexpected.

Changing Regime of Knowing. The lure, however, is real: We are currently embedded in an academic system largely structured by the regime of quantification (Espeland & Sauder, 2007). Quantifiable outcomes such as the number of publications, citations, etc. undoubtedly shape valuation schemes in academia and as a consequence the academic practice. I can see the lure of generative AI becoming even more real given its promises for efficiencies. In other contexts, AI is already becoming the default way for processing documents. For example, judges are already reported to slam attorneys for not using AI in legal research to reduce the fees they charge (LexisNexis, 2023). I will not be surprised if academic targets are heightened with the assumption that scholars can produce faster results with the help of generative AI tools. Instead, I am concerned about how we will ensure we maintain originality and depth in our thinking if that becomes the case. A non-native English writer could use ChatGPT to find the right word to use in a sentence. They may even replace the thesaurus with ChatGPT. But they will most likely spend significant time interacting with the tool until they edit the phrase/sentence in the way that makes the most sense to them. As in other cases of augmenting work practices with AI (Lebovitz et al., 2021; Pachidi et al., 2021), generative AI tools cannot replace the work performed by human experts.

We are on the cusp of a paradigmatic change; what I would call a potential change in our regime of knowing: with generative AI challenging and potentially shaping what kind of knowledge matters, how it is produced, and who has authority to shape it (Pachidi et al., 2021). This is the time to reflect on our academic practice and decide what matters in organization and management scholarship, how we value it and how we will maintain it.

Chatty actors: Generative AI and the reassembly of agency in qualitative research

Vern L. Glaser and Joel Gehman
University of Alberta and George Washington University

"An actor is what is made to act by many others."

"Remember that if an actor makes no difference, it's not an actor."

– Latour (2005: 46; 130)

Talk of generative artificial intelligence (AI) and large language models (LLMs) such as ChatGPT has become ubiquitous. Building on the invention of the novel Transformer network architecture (Vaswani et al., 2017), LLMs are able to generate text through prediction models that incorporate billions of parameters, have been trained on massive texts, and feature the ability to do in-context learning, instruction following, and step-by-step reasoning (Zhao et al., 2023). In turn, humans utilize LLMs by engaging in different types of "prompting" techniques (Wei et al., 2023) or "fine-tuning" methods that use focused human feedback as a means to elicit desired results from the LLM (Christiano et al., 2023; Ouyang et al., 2022). The intuitive natural language interface and human-like responsiveness of LLMs thus have the potential to profoundly reshape human and machine interactions (Kennedy & Phillips, 2023; Murray et al., 2021).

In addition to their many other applications, LLMs and other generative artificial intelligence (AI) technologies offer the potential to dramatically impact the research process. Already, enthusiastic and entrepreneurial faculty have promoted the transformational benefits of the technology, with some offering seminars on "Using ChatGPT for Automated Literature Review[s]," "Using ChaptGPT for Academic Publishing," and "Using ChatGPT for Automated Grant Writing" (Instats, 2023). At the same time, skeptics question the utility of these tools, suggesting that "researchers embracing ChatGPT are like turkeys voting for

Christmas" because reliance on AI will "deskill the mental sphere" and "impoverish … theoretical and analytical skills" (Lindebaum, 2023).

In this essay, we explore how generative AI can contribute to qualitative research by examining its potential to reassemble agency (Gehman et al., 2022; Glaser et al., 2021; Latour, 2005). Specifically, we suggest that the affordances of LLMs and generative AI facilitate three distinct ideal-typical agentic possibilities: Generative AI as a *research assistant* that supports researchers by functioning as an administrative assistant and interactive conversation partner; generative AI as a *data analyst* that can be programmed by the researcher to analyze data with enhanced, dynamic pattern recognition; and generative AI as *co-author* that can act as a semi-autonomous agent in the pursuit, discovery, and refinement of new knowledge. Paralleling these three modes of actorhood, we introduce three principles of governance that management researchers can embrace to mitigate against the potential abuses of generative AI (see Table 1).

Generative AI as Research Assistant

The interface for LLMs, popularized by OpenAI's product ChatGPT, is the *prompt* (Glaser et al., 2023). ChatGPT uses "interactive forms to provide detailed and human-like responses to questions raised by users" that can handle a variety of tasks including "text summarization, text completion, text classification, sentiment, analysis, translation, etc." (Zhang et al., 2023, p. 5). A researcher can engage in interactive prompting by integrating some simple principles that can enhance the assistance provided by the LLM, such as providing the LLM with a perspective, tasking it to write in a certain style, or seeking for specific information on the internet (Mollick, 2023a). These capabilities can be incredibly useful to anyone, particularly researchers, and as such ChatGPT or Bing's GPT-4 enabled browser have been described as having access to your own "AI intern" (Mollick, 2023b).

To explore the possibilities that this powerful feature affords, we looked back to our previous research and brainstormed about how an LLM might have helped us advance our research process. For example, one of the challenges in Glaser et al.'s (2016) study of online advertising was trying to understand the language used in the world of online display advertising, as the empirical context was complex and challenging to understand. Retrospectively, we asked ChatGPT Plus some questions about the empirical context that would have been useful to understand, and we found that ChatGPT Plus provided superficial but accurate synopses of the data, providing useful background information.

From a research perspective, it is important to recognize that there are limitations on such output generated by LLMs, such as "hallucinations…where the generated information is either in conflict with the existing source data (intrinsic hallucination) or cannot be verified by the available source (extrinsic hallucination)" (Zhao et al., 2023, p. 26). Although it is likely that this problem will become less severe as generative AI techniques advance, clearly the theoretical arguments underlying scientific knowledge claims must be accurately represented. We therefore suggest that scholars using LLMs as a research assistant follow the principle of *citation*: whenever data is used, the original source should be cited. Note, we are not suggesting it is necessary to continually cite the LLM itself; rather the researcher should cite the appropriate original sources. For instance, in the case of Glaser et al.'s (2016) study, the resulting timeline could reference the original source documents and materials surfaced by ChatGPT Plus.

Generative AI as Data Analyst

Underlying LLMs is the capability of recognizing patterns, which also is one of the core principles of qualitative research (Glaser and Strauss, 1967; Kelle, 2005). Although much public attention has been paid to the tendency for LLMs to "hallucinate" (Edwards, 2023), it is likely that these tendency can be—and are already being—rapidly adjusted through the process of targeted reinforcement learning from human feedback (RLHF) (Christiano et al., 2023; Ouyang et al., 2022). Behind the scenes, LLMs can be "tuned" in two important ways: the performance of the model can be improved through "instruction tuning" and the "values" of the model can be improved through "alignment tuning" (Zhao et al., 2023, pp. 15–20). The performance of LLMs in pattern recognition also can be enhanced through more complex prompting such as "chain-of-thought" prompting (Wei et al., 2023) and "tree-of-thought" prompting (Long, 2023). Complex prompting and RLHF capabilities of generative AI will only increase over time, and these affordances will provide researchers with powerful ways to advance their research.

As RLHF becomes more sophisticated, one can imagine situations in which the researcher programs the algorithm to engage in very specific coding activities. One can imagine using chain-of-thought prompting to identify different potential codes of interest, and then tasking the AI data analyst to identify all the instances of those different options. It even seems possible that the AI analyst might identify further categories or examples that human coders missed. In many ways, generative AI offers qualitative researchers the opportunity to apply the constant comparative method (Strauss & Corbin, 1998) in faster, more comprehensive, and more novel ways.

In governing the role of generative AI as data analyst, the principle of citation does not go far enough. And, citing the LLM itself is not necessarily going to allow replicability, as the algorithmic nature of generative AI produces different results for the same prompt (Zhao et al., 2023). Consequently, we need to move beyond citation, and thus introduce the principle of *transparency*: the researcher should clearly articulate the steps taken in their analysis. In the case of prompting, this would require documenting the prompts used, even in their complexity (this may require the use of appendices in papers). In the potentially future case of scholar-tuned RLHF techniques, this might require detailed description of the tuning practices implemented by the researcher.

Generative AI as Co-Author

With these capacities, can LLMs ultimately be considered a co-author? In the first two methods of reassembling agency, generative AI serves to augment researcher capacity, but stops short of making independent contributions. However, computer science research is already introducing “generative agents” which are computationally powered and “can serve as believable proxies of human behavior” (Park et al., 2023, p. 2). This “agent architecture” consists of three components: a memory stream that reflects the agents’ experiences, reflections which “synthesize memories into higher-level inferences over time, enabling the agent to draw conclusions about itself and others to better guide its behavior” and planning ,which translates this analysis into “high-level action plans” and “detailed behaviors for action and reaction” (Park et al., 2023, p. 2). This architecture has the potential to allow for agents to engage in “role-playing” which can help develop cooperative behaviors between different AI agents in multi-agent systems (Li et al., 2023).

At the moment, generative AI is still in its infancy, an early-stage technology. It is not clear the “dominant design” has yet emerged (Anderson & Tushman, 1990). But already there are signs that generative AI could represent a general-purpose technology with the potential for widespread impacts—akin to gunpowder, the printing press, electricity, or the internet. Relative to the research process, one potential is that in the future we will all have our own AI doppelgänger, a specially “tuned” agent that can finish our sentences for us. Or, perhaps even more provocatively, write entire papers in conversation with us.

For the next generation of Ph.D. students, perhaps this happens in real-time alongside the seminars they are taking. For instance, imagine training your personal GPT agent using the comprehensive exam questions and answers from prior cohorts of your department, feeding it all of the articles and article summaries you and your classmates generate each week as part of your seminar preparation, giving your AI agent redline edits of your advisor's comments on drafts of your papers, and so on. All of this seems well within reach—even without this effort, existing LLMs can already help emulate your voice.

But generative AI also raises new questions about research ethics. As discussed above, it is already possible to discern the emergence new AI-related disclosure practices consistent with scientific norms—i.e., communalism; universalism; disinterestedness; originality; skepticism (e.g., Merton, 1973; Ziman, 2000). But from a governance standpoint, the possibility of co-authorship begs a more fundamental question: how should institutional review boards (IRBs), which are ubiquitous within universities, respond to the use of generative AI in the research process? It seems clear that IRBs will need to devise new heuristics for the AI era.

Conclusion

Clearly, generative AI and LLMs are actors: they are "made to act by many others" (Latour, 2005: 46). Increasingly these "others" include academics. At the same time, it seems clear these new AI agents have the potential to make a considerable difference in how research is conducted, which is at the very heart of what it means to be an academic. All of this novelty and concern provides fertile research terrain for organization and management scholars, and it seems to us that we will be well served to maintain a reflective posture that considers how these reconfigurations of modes of assembling agency influence values (Lindebaum et al., 2022) and reinforces the importance of doubt to the research process (Weick, 1998).

Table 1 – Ways of Reassembling Agency in Qualitative Research

Agentic Mode	**Focal Capability**	**Research Affordance**	**Governance Principle**
Research Assistant	Simple prompting	Interactive conversation partner and administrative assistant	Citation and verification
Data Analyst	Complex prompting and tuning	Enhanced dynamic pattern recognition	Transparency and trustworthiness
Co-Author	Generative agents	Open-ended, goal-focused exploration	Institutional Research Board (IRB)

Large Language Models might displace inductive scholars—but they will not replace us.

Gianpiero Petriglieri, INSEAD

Since the children became old enough, it has been our family's tradition to take a short bike tour in a different part of France every Spring. Nothing athletically ambitious. We are in it for the fresh air, the warm croissants, and the wonders of this country where we have made our home. On one such tour in the Périgord region, a few years ago, Jennifer, the kids, and I cycled past the village of Montignac and followed signs to the cave complex of Lascaux. This UNESCO World Heritage site is the product of human curiosity, ingenuity, and chance. The caves were discovered in 1940 by a teenager, Marcel Ravidat, who was walking his dog in the woods surrounding the village when he noticed the opening of a tunnel. He thought he had discovered a medieval secret passage and enlisted three friends to explore it. But after a short descent into the ground, the foursome found themselves in a large cave complex instead, densely decorated with hundreds of perfectly preserved prehistoric rock paintings that had not been gazed at, historians later estimated, for 17,000 years.

The Lascaux caves soon became a sensation. After World War II, tourists could visit them for a decade or so. But the paintings proved too fragile to withstand the carbon dioxide and micro-organisms that came with hundreds of visitors per day. Hence their location is unmarked and off limits today. The road signs lead to a modern visitor complex nearby. Once there, we lined up to tour Lascaux IV, the latest and most accurate reproduction of the caves opened to the public in 2016. Despite the knowledge that we were not really seeing the original rock art, I could not help being awe struck in the dimly lit space. I was impressed by the verisimilitude of the replica and inspired by the drawings. I imagined someone entirely like me and entirely unlike me at once, a human in a different time and space, sketching those scenes, laboring to leave their fingerprints on the rock. And other people like me and unlike me too, later using their tools to augment—and monetize—those original printed rocks.

It is safe to assume that those who painted that pantheon of paleolithic animals in the Lascaux caves had no modern conception of authorship. And since they have long been dead, it is impossible to know what moved them to draw—to scrutinize the motives or meaning of their work. But I didn't need that knowledge to be moved by the work's existence, to recognize it as an expression of the human impulses to document and create, unprompted. A tour guide told us that the Lascaux paintings might have been a form of accounting, a record of the species that populated the area at the time. Or that they might have been a form of visual art, the décor of a sacred space where hunting rituals were once held. I prefer to believe that they were both at once, the records of artful hunters accounting for themselves.

Of course, I would. Given my field of work, leadership research and education, I am aware of the thin line between the functional and the expressive, between duty and desire, between the need to reach our goals and the wish to articulate our selves. Leadership is just shorthand for the ability to combine the two credibly, for a while. I might work at a school of management in the 21st century, but I am surrounded by colleagues and students, scholars and managers, authors of text and things who, like me, are animated by the impulses to account and to create. Like the rock painters in Lascaux, we are all moved to leave our fingerprints on the rock before our fingers stop and turn to dust. And if we are good, and lucky, our accounts and creations might survive us. At our best, we build to last.

Within that field, I am an inductive scholar. I try to account for places and people I have engaged with, in ways that might help others who encounter similar places and people. Put another way, I craft theories out of stories. To come up with good theories, I first need to partake in good stories. And then I need to free myself up enough from those stories to abstract plausible conceptualizations. Sensitivity and sensibility, as I see it, are the pillars of inductive research. One lets us encounter the world, the other theorize about it. We need to honor our senses, then, for our theories to make sense. Especially if we aim to humanize organization theory (Petriglieri, 2020), leadership (Petriglieri & Petriglieri, 2015) and management (Petriglieri, Wood, & Petriglieri, 2011) development, that is, and make them account for the experiences of conflicted people in complex contexts (Petriglieri & Petriglieri, 2022). If we aim to grasp and reveal how work shapes people, and vice versa, we must start with how our work shapes us (Amabile & Hall, 2021; Petriglieri & Ashford, 2022).

Enter ChatGPT and other Large Language Models (LLM)s. How much more efficient and focused I could have been if I had used one of those tools to help me with this piece, instead of hesitating after the editor's invitation, procrastinating despite his gentle nudges, and meandering through five paragraphs of metaphorical musings. Instead, I chose to interrogate my hesitation and take you along on my meanderings. I hesitated because I don't feel qualified (here goes, I said it) to write about a tool (or is it an entity?) that I have little enthusiasm for. And I meandered because… well, if you know me, that is how I write. Yes, I have tried ChatGPT. I have just not loved it. Hence my difficulty. I can't write much or well without love. LLMs might help some scholars. But they can't help me. They do not sense anything before they write and do not sound like me when they write. And if I cannot sense and sound like me, I cannot know things and you cannot know me. Then I'd rather not write at all. Because such writing might be efficient and clever, but it is neither grounded nor free.

Inductive research requires a combination of compliance and defiance. Like the cave painters of Lascaux, we must be compliant with the truth, taking great care when collecting and reporting the experience of informants. And we must be defiant with our theories, taking great care to develop our own inferences. We need compliant sensitivities and defiant sensibilities to craft grounded theories. Cultivating both requires discipline, and that discipline, in turn, gives us a unique identity that we manifest in our scholarly work. Like all identities, our scholarly identity is forged in relations with informants and colleagues, students, mentors, and critics—not just with ideas and tools (Pakarinen & Huising, 2023).

And it is refined by adopting technologies that let us express our selves at work, and rejecting those that limit our choices for efficiency's sake (Nelson, Anthony, & Trispas, 2023).

In my tentative forays, I have found ChatGPT compliant and defiant too, but in all the wrong ways. It complied to every request of mine, and yet defied the truth at times. I have asked it to draft the framing for an academic paper, and a literature review for another. It did what I asked, at first glance. But when I looked closer, I found that some of the references that made the argument flow were fabricated. I have asked it to edit a piece for a practitioner's magazine, and it made me sound like a corporate press release. It didn't seem to care too much for truth or voice. If it had been a human, and I could have inferred its motives, I would have said it didn't try to please me as much as to appease me.

Why wouldn't it? All AI-based tools, and LLMs are no different, are technologies whose (makers') success rests upon on pleasing, predicting, and producing us (Chamorro-Premuzic, 2023). The more time I spend on Instagram, say, the more its AI learn to make my stream appealing, and the less likely I am to take a walk on the beach instead of scrolling. And as I keep scrolling, I am not just confirming AI's predictions of what images I like, I am conforming to its production of an "intellectually sedated" (Chamorro-Premuzic, 2023: 33), emotionally appeased, hence more easily captive subject. Likewise, the more I learn to prompt LLMs, the more they might become useful and maybe necessary for my work.

I find that concerning. A tool that captures scholars in exchange for more efficiency will inevitably enhance the instrumental forces that are already dehumanizing academia and alienating academics, rendering us unable to "be astonished afresh by the ordinary," and write "with a little more humor, curiosity, and passion" (Tourish, 2020: 108; see also Courpasson, 2013; Fleming, 2020; Howard-Grenville, 2021; Petriglieri & Ashford, 2023). ChatGPT and the LLMs of OpenAI's competitors will augment one thing: the influence of those who conflate productivity with efficiency, helping them turn academia into a world in which being called ‘a machine’ is more often a compliment than an insult. A world in which knowledge is the product of calculations more often than of relationships. “Before we worry about the machines that are coming, then,” I remain convinced that we must “worry about the machines we have become” (Petriglieri, 2020: 8; see also Chamorro-Premuzic, 2023).

The academic work that ChatGPT and its enthusiastic users will produce might be impressive for its verisimilitude, like the modern Lascaux replica. But it will not be as inspiring as the prehistoric artful accounting. In time, we might lose the ability to tell them apart. As we are forced to catch up and interact with and through technology, rather than helped to stand still and to get close enough to other people in our fields, we might lose the capacities and connections necessary to question our work and that of others, as well as the work produced by artificial intelligence (Lebovitz et al., 2021). It will get harder to sustain a discipline based on compliant senses and a defiant sensibility, and it will be easier to submit to the kind of discipline that makes us docile and captive instead. LLMs might make scholars more productive, then, and less human, that is, at once producers and products of creative impulses that draw our selves out in the world and into our work. In doing that, LLMs might displace scholars like me, but they will not replace us. Not until they can go for a wander and get distracted by a passage to another world, still full of awe.

Three provocations - ChatGPT undermines ‘learning’ to theorise, homogenizes theory, and distorts competition for the best ideas in management research

Dirk Lindebaum
Grenoble Ecole de Management

LLM assistance statement: GPT-4 and ChatGPT were used for writing, coding, and formatting assistance in this project (Eloundou, Manning, Mishkin, & Rock, 2023).

Writing about the future of management research in a ChatGPT world invites speculation concerning the space between *what is?* and *what will* or *could be*? However, given the pace of articles published in recent months within academia and the news (see Zhang et al., 2023, for a review), it appears that the future is already here with a vengeance, and management scholars ignore at their own risk the deep transformations afoot in terms of what kinds of knowing and knowledge will emerge from this. As the introductory quote suggests, in disciplines like computer science or information management, ChatGPT effectively acts already as co-author (see also Laumer, in Dwivedi et al., 2023), underlining concerns that the move from ‘manuscripts’ to ‘technoscripts’ is already under way (Lindebaum & Ramirez, 2023). Further, ChatGPT is already used or advocated in the research process in relation to scientific writing, brainstorming, literature reviews, data analysis, direct content generation, grammar checking, and serving as an academic reviewer (Zhang et al., 2023). These applications are plausible, as ChatGPT represents a ‘state-of-the-art’ large language model (or LLM - Eloundou et al., 2023). These models refer to “systems which are trained on string prediction tasks: that is, predicting the likelihood of a token (character, word or string) given either its preceding context or (in bidirectional and masked LMs) its surrounding context . . . when deployed, [they] take a text as input, commonly outputting scores or string predictions” (Emily M. Bender, Timnit Gebru, Angelina McMillan-Major, & Shmargaret Shmitchell, 2021, p. 611)[1].

[1] For more background, see https://openai.com/blog/chatgpt

My contemplations here depart from the 'techno-enthusiasm' around ChatGPT as applied in management research. Specifically, based on practical concerns around the deleterious effects of using ChatGPT as a 'research tool', I develop three provocations to theorize why these deleterious effects arise. First, ChatGPT affects our ability to 'learn' as theorists, especially the human capacity to express itself in creative social science research in ways that harnesses *imagination for a better future* (rather than predictions based on existing data). This, I argue, can be important for linking observed phenomena with theoretical explanations or understanding for improved future practice. While some writers argue that the very use of AI and ChatGPT can *aid* researcher creativity (e.g., Amabile, 2019), an in-depth epistemological critique suggests that this assumption needs to be taken with a pinch of salt. This is because ChatGPT offers high-probability rather than low-probability choices *within* a data set, let alone any choice *outside* the training data set (Lindebaum & Fleming, forthcoming). Note that the emphasis on high-probability choices also implies that 'mainstream' and 'dominant' strands in the training data are more likely to be picked up, a tendency rather antithetical to creativity. Second, ChatGPT changes the mode and speed of theorizing in management research, given its focus on reckoning/formal rationality in producing outputs rather than judgement/substantive rationality (Lindebaum, Vesa, & den Hond, 2020; Smith, 2019). This is not to say that AI applications have no merit – far from it, if we only think about the benefits in medical research. However, I am not sure that there is sufficient appreciation in current debates on the ontological foundations of different decision-making frames (i.e., based on formal or substantive rationality) that inform our theorizing (but see Smith, 2019 for a rare exception). Third, and being potentially fostered by the former points, ChatGPT distorts the conditions for a fair and truly competitive marketplace for the best ideas in management research. This point matters for both (in)transparent uses of ChatGPT in light of publications not only being scientifically valuable, but also being significant for career progression and status (Aguinis, Cummings, Ramani, & Cummings, 2020). I close this essay with reflections on being seduced by the 'gold rush' (my words) for greater research productivity (Dwivedi et al., 2023; instats, 2022), and that 'speed and efficiency' (Zhang et al., 2023) as hallmarks of scientific progress carry significant risks, especially when LLMs are inherently biased to perpetuate dominant viewpoints (Emily M. Bender et al., 2021) and subject to so-called 'hallucinations', or simply creating 'false facts'[2].

Provocation #1: ChatGPT affects our ability to 'learn' as theorists to better link observed phenomena with theoretical explanations/understanding for improved future practise

One crucial way through which the use of ChatGPT affects our ability to 'learn' as theorists is due to it impoverishing our analytical skills and imagination when applied for reviewing the literature and the writing of articles *per se*. It does so by discouraging our own 'reading for understanding' (Adler & van Doren, 1940/1972), and ignores the fact that insight and analysis often occurs during the process of writing.

As to reading for understanding, or lifting oneself "*from a state of understanding less to one of understanding more*" (Adler & van Doren, 1940/1972, pp. 7, italics in original) through the power of one's *own* mind, this has enabled me, over time, to see and make more and new theoretical connections that I hope are perceived as making a relevant contribution to the literature. To paraphrase Adler and van Doren, unlike obtaining a direct response from ChatGPT (rather than a teacher), if we "ask a book a question, [we] must answer it [ourselves]. When [we] question it, it answers [us] only to the extent that [we] do the work of thinking and analysis [ourselves]" (1940/1972, p. 14). Therefore, reading for understanding involves the willingness to overcome a preliminary inequality of understanding between a reader and author (e.g., when a doctoral student reads a monograph). By contrast, the use of ChatGPT discourages our attempts to overcome any inequality between a text and us – it

[2] See https://www.theguardian.com/commentisfree/2023/may/08/ai-machines-hallucinating-naomi-klein (accessed on 17 May 2023).

simply serves ‘food for thought’ that can be past its best-before date. After all, in a recent simulation of ChatGPT to ascertain its proximity to human intelligence, the authors note that what AI is arguably missing is the part on “learn[ing] quickly and learn[ing] from experience”, because the model is not continuously updated (Bubeck et al., 2023, p. 5).

In addition, writing is also a very important conduit for spontaneous insights and clear thinking. Rather regularly, the Gordian Knot of a theoretical kind has been untied through writing as opposed to thinking only. And it makes sense to argue that attending to our written words also helps clarify our thoughts. After all, in linguistics, writing is the product of transcription, executive processes and text generation – the latter involving translating *ideas* into written language (Babayiğit & Stainthorp, 2011). Combined, these two angles underline how reading for understanding and writing ourselves are central for truly creative theorizing for novel and *forward-facing* thinking. Naturally, then, I have grave reservations about ill-conceived arguments that “writing text may no longer be a crucial component of scholarly work, as this task can be supported more efficiently by tools like ChatGPT” (Laumer, in Dwivedi et al., 2023, p. 24).

Provocation #2: ChatGPT changes the mode and speed of theorizing in management research, given its focus on reckoning/formal rationality in producing outputs rather than judgement/substantive rationality

As indicated, LLMs (like ChatGPT) operate by statistically predicting the likelihood of the next word in a text. LLMs resonate, therefore, with an ontological view of the world based on reckoning, or the “the calculative rationality of which present-day computers … are capable” (Smith, 2019, p. 110) by processing data through an accumulation of calculus, computation, and formal rationality (Lindebaum et al., 2020). Thus, when ChatGPT is applied to write a scientific text, or even to theorize, it likely reproduces said ontological viewpoint, a viewpoint that impoverishes theorizing due to a tendency toward ontological monism of constructs (Lindebaum, Moser, Ashraf, & Glaser, 2023), and the ontological straightjacketing of judgment into reckoning. And it does so with a click of the mouse. By judgment, I mean decision-making sensitive to "the social and historical context and different possible outcomes . . . [judgment] implies not only reasoning but also, and importantly so, capacities such as imagination, reflection, examination, valuation, and empathy" (Moser, den Hond, & Lindebaum, 2022, p. 139). Modes of theorizing, found, for instance, in academic essays, are being challenged[3]. After all, as Gabriel (2016) notes, "relishing thought experiment, the essay frequently assumes the role of devil's advocate; it encourages the suspension of disbelief, it delights in paradoxes, it tests boundaries and questions assumptions" (p. 245). With a nod to Adorno, Gabriel (2016) also highlights that essays transgress the orthodoxy of thought to reveal that which orthodoxy tries to hide. Yet, LLMs are the epitome where such transgressions are quintessentially necessary, for LLMs reproduce and encode "stereotypical and derogatory associations along gender, race, ethnicity, and disability status" due to biased training data (Emily M. Bender et al., 2021, p. 613)[4]. This development must be seen in the wider context of the 'privatization of speech technologies', where only a handful of tech firms produce LLMs (Bajohr, in Neumann, 2023). If we are "unduly impressed by reckoning prowess", Smith (2019, pp. xix-xx) warns, there is a risk that "we will shift our expectations on human mental activity in a reckoning direction". This observation applies to theorizing as a human mental activity as well.

Provocation #3: ChatGPT distorts the conditions for a fair and truly competitive marketplace for the best ideas in management research

Apart from being scientifically valuable, publications also matter much for career progression and status in academia. However, if we heed the aforementioned premonitions on how challenging learning to theorize can be, and what modes of theorizing might ensue in a

[3] This is not to say that using ChatGPT for the production of scientific 'technoscripts' may not be problematic for theorizing in the rationalist and empiricist tradition. However, exploring these angles here is outside the space available here (but see Lindebaum, Moser, & Glaser, 2023).

[4] Further, these models are not inclusive: "over 90% of the world's languages used by more than a billion people currently have little to no support in terms of language technology" (Emily M. Bender et al., 2021, p. 612).

ChatGPT world (because these modes of theorizing are faster), it is not difficult to discern how (in)transparent uses of ChatGPT in the research process – from beginning to the end – distort the idea of an unaided and original accomplishment. Couple this with the difficulty of obtaining permanent or tenured posts (Trinh, Kirsch, Castillo, & Bates, 2022), conditions are created to skip the hard thinking and writing work that normally goes into writing a well-crafted paper. I am entirely unimpressed by attempts to 'assuage' concerns about human authors remaining in charge for ChatGPT becomes only a 'collaborative tool' so to speak (see also Laumer, in Dwivedi et al., 2023). The point worth heeding is that, at the end of the day, even if the use of ChatGPT is transparently declared, it is difficult if not impossible to tease out the variance in the paper produced by a human or ChatGPT. Again, examples like the opening quote fail to disclose exactly how much the idea-generating and output-producing efforts can be attributed to humans or ChatGPT. Some years ago, through perseverance and dedication to reading for understanding and writing myself (together with human co-authors), we managed to turn a 15-page high-risk decision letter for an essay into an acceptance letter. That experience is *ours*, and it is invaluable for pushing the frontiers of knowledge with each subsequent project.

In sum, the momentum behind the exponential use of ChatGPT means that the technology is here to stay – the genie is out of the bottle. While I appreciate how valuable technological advances can be when the decision-making frames call of reckoning rather than human judgment, applying the idea of reckoning as an enabler of creativity is likely to impoverish rather than enrich theory in future. What may well prompt current 'techno-enthusiasm' to become future 'human ignorance' is the fact that, through a process of 'learned helplessness' and the deskilling of the mental sphere (Friedland, 2019; Lindebaum & Ramirez, 2023), that we, as theorists, lose the ability to explain and understand the social world. The fact that intelligence levels in the general population have been decreasing for some time in the general population (Rindermann & Becker, 2023), while the use of technology increases, gives me cause for concern here, especially in the context of management learning (Lindebaum, 2023). While I agree with others when they claim that “the need to understand how new ideas . . . are created . . . has never been greater for academics” (Sætre & van de Ven, 2021, p. 1), I also fear that the human role in theorizing new ideas is going to be diminished soon. Who wants to be an accomplice in normalizing theorizing based on reckoning and formal rationality only? Don’t count me in on this issue.

Large Language Models in Qualitative Research: Not all that Glitters is Gold

Lindsey D. Cameron and Hatim A. Rahman
Wharton School, University of Pennsylvania and Kellogg School of Management, Northwestern University

Large language models (LLMs), such as OpenAI's ChatGPT and Google's Bard, have generated a palpable buzz, including among qualitative researchers (Xiao et al., 2023).[5] Many have experimented with using these systems to code and summarize their data and even write parts of their paper, such as an introduction, literature review, and finding's section. The fact that these systems can potentially help with these tasks has many researchers salivating at the prospect of using LLMs to enhance, and even speed along, the notoriously slow qualitative research process. Yet, as we argue below, the seemingly impressive LLM capabilities belies a more complex reality. LLMs fundamentally excel at providing statistical relationships between data it has been trained on (Bender et al., 2021). However, qualitative research has never been about trying to determine the statistical probability of different themes collected from one's field notes, interviews, or archival data. Rather, the goal of qualitative research, especially in management research, is to uncover novel themes and generate new theory (Charmaz, 2006). At its core, this process involves an iterative process between collecting and analyzing qualitative data, including making connections between what is missing in one's notes and observations with what one has observed in a social setting (Grodal et al., 2021).

To expand, quantitative and qualitative research are different (and valid!) ways to understand social reality. Quantitative is variance-reducing, focusing on understanding the average or mean experience. Reams of statistical tools remove outliers, calculate statistical significance (within socially constructed limits), and verify replicability. In contrast,

[5] Our essay will focus on discussing LLMs generally, rather than a specific LLM owned by a company (e.g., OpenAI's ChatGPT, which Microsoft has invested in)

qualitative research is variance-seeking.[6] When qualitative researchers go into the field, we are purposefully seeking to observe a wide range of human experiences and practices. Numerous "how to" books, outline interview techniques on how to ask grand and mini-tour questions, asking various questions types (e.g., contrast questions, q-sorting, 'tell me a time'; Weiss, 1995) or, in ethnographies, to visit the context in varied situations/people/contexts (Spradley, 1979, 1980). Indeed, many qualitative papers call their cases an 'extreme case' and initial ideas are seeded by a unique piece of data (Eisenhardt 1989; see Whiteman & Cooper 2011 and Creed et al., 2010 for examples).

In the rest of the essay, we want to highlight three areas scholars should carefully consider in how using LLMs, even in an attempt to enhance (rather than automate), in the qualitative research process can produce unintended effects: data analysis, reviewing the literature, and developing skills as a new scholar.

Data Analysis: Finding the Surprise. A hallmark of qualitative research is the "surprise" – the turn of phrase, unusual experience, or chance observations that both confounds and delights the scholar. Christianson (2011) elegantly described a surprise in qualitative data analysis as *moments of confirmation* and *moments of disconfirmation,* that frequently becomes a touchstone in the iterative analysis process. To find these surprises, seasoned scholars urge us to stay alert and do "live" coding (Locke et al., 2015). A surprise to an LLM, however, constitutes a word or concept with the lowest frequency or using *existing* data it has been trained on to highlight what may constitute a surprise. A statistical surprise based on prior data, however, is not what a surprise means in qualitative research. Part of what guides researchers to be able to discern surprises is the non-linear, embodied nature of qualitative research in which researchers seamlessly tack between collection and analysis

[6] Please note this essay is not trying to diminish the purpose or nature of quantitative research. In certain settings, (e.g., medical trials, stress testing of building materials), randomized controlled trials and understanding effects to the mean population are, indeed, quite critical and needed.

(Locke et al., 2022). Often on the first day in the field, researchers often “find” their hologram – the one piece of data that exemplifies an empirical puzzle – and the next six months to two years of data collection is adding flesh to the bones. For example, in Cameron’s (2022) paper on workplace game, the surprise was workers' enjoyment of the work, which countered the prevailing narrative of alienation (which was the data the LLM would have trained on) and her own personal experience. Often, these puzzles become metaphors that fundamentally depart from prior conceptualizations, such as the “invisible cage” (Rahman, 2019), the “task bind” (Feldberg, 2022) or “relational spaces” (Kellogg, 2009).

Moreover, surprise is often in the eye of the beholder. Take for example the Mann Gulch Fire which has been studied by at least half a dozen management scholars and many more in other disciplines. Weick (1995) and Whiteman and Cooper (2011) use a sensemaking lens centering human agency to understand the disaster while Jensen and Mahmud (2023) take a different perspective that decenters sensemaking. Even within the same paper, scholars can reanalyze their own data, unearthing different surprises, and coming to different conclusions such as in the artivle by Sutton and Rafelli (1988). Such surprises are intimately tied to the emergent, embodied data a researcher collects and the iterative collection/analysis process, not to the statistical distribution of the words written in text.

Literature Reviews: Creating New Bridges Between Literatures. As noted, LLMs excel at providing statistical relationships between data they have been trained on. Many have highlighted how this can potentially speed up the process of reviewing and analyzing prior literatures, including using LLMs to find “gaps” between literatures and suggesting novel research questions. As already mentioned by several authors in this special issue, we want to highlight that reading and summarizing an article is much more than simply articulating what points are written in a text. The act of reading any text involves reflection, contemplation, and making connections with one's own experiences, assumptions, and knowledge. In-depth and, at times, creative interpretations of literatures are particularly important for qualitative research, which often sparks completely new lines of research. Take for example Tislick and colleagues (2015) carving out a new literature on concealable stigma and occupational segregation, or Dutton and colleagues (2006) who synthesized multiple literatures to bring forth the new field on the study on compassion and organizations. More recently, Rahman and colleagues (2023) bridged the management and sociology literatures on experimentation to study the social effects of experimentation. None of these award-winning works would have been achieved without a close yet novel bridge between different literatures. Often, this bricolage between literatures, is the hallmark of novel, theory-building papers that spark an entire new field of inquiry, and not something that can easily be reproduced by a statistical model.

Further, two people can read the same exact text and come up with very different answers to what the main argument of the text is. These differences in reviewing and synthesizing literature are not "right" or "wrong," but highlight the essential subjective, human experience that comes with reading a text. Much like "sparknotes" never replaced the experience and value of reading a book, relying on LLMs to conduct literature reviews may be helpful in some regard, but should not be relied on to replace reading and reflecting about literature. In other words, reviewing literature is not a defined, static task, but instead is the result of a creative bricolage by the authors who often pull together several disparate threads.

Learning the Craft: Developing as a Qualitative Scholar. Too often in our time-starved economy, we equate time with money and speed with quality. Increasingly, academics have challenged this rhetoric, highlighting that "slow is the new fast" (Berg & Seeger, 2016). We worry that, overall, the temptation to use LLMs (and other AI tools) might have short-term productivity gain but will dampen, overall, the quality of academic thinking, especially for qualitative scholars who rely on iterative thinking, embodied knowledge, and serendipitous insights. In other words, just because an LLM can help in the research process, it does not mean we should use it to help.

Nowhere is this more important than in doctoral programs, when scholars are grappling with learning research methods as well as developing content expertise, which makes the usage of LLM tools especially tempting. Yet outsourcing, or at least attempting to outsource portions of qualitative research, may be detrimental in the long-term if budding scholars cannot build up their embodied knowledge, skills, and research chops. Other professions have heeded this lesson, which we can learn from. For example, even though software has been able to automate a large portion of flying commercial airplanes for years, new pilots are still extensively trained on the ins and outs of manually flying a plane. This training ultimately provides a better understanding of the strengths and limitations of the automation software (and how to operate in case the software fails!). Similarly, in the age of AI and LLMs, we still see a strong impetus for doctoral students to engage in the "classic" qualitative training approach to ensure they can better understand when an LLM can and cannot help in the research process.

Confronting the Ethical Consideration for Qualitative Methods. We want to also highlight that many researchers have raised serious ethical concerns with regards to using the most popular, accessible LLMs, such as ChatGPT and Bard (Fiesler, 2023). Among the issues they have highlighted, include these companies training their models on people's data without their permission (or providing credit and compensation), using underpaid workers to refine their models (Perrigo, 2023), and disregarding other emerging laws and regulation (Gregorio & Pollicino, 2023). Further, reports have highlighted that these popular LLMs models infringe upon copyright (Campbell, 2023), consume significant natural resources thereby exacerbating climate change (Saenko, 2023), and can still be used in ways that cause harm.

For qualitative researchers, we want to add two additional considerations. First, qualitative data often contains confidential information. Entering sensitive information into a commercial LLM could allow the LLM to train and reuse this data (without permission), thereby compromising the confidentiality of the data. Second, LLMs can more easily be used for fabricating qualitative data. While we will not elaborate on the ways in which this can be done, qualitative researchers need only to look at recent cases of research misconduct to hopefully discourage such type of behavior. Nevertheless, we remain concerned that, as a field, we do not have the proper systems in place to adequately discourage (and catch) such unethical use of these systems.

Scholars have long highlighted that a technology's capabilities do not determine how a technology is used or the impact it has (Barley, 1986; Orlikowski, 1992). Rather, the implementation and impact of a technology reflects the power, culture, values, roles, and other social factors in a society, organization, and community (Noble, 2018). In fact, researchers have uncovered new, unanticipated capabilities when people use new technologies, including with AI (Amabile, 2020) Thus, as much excitement (and fear) there is about LLM capabilities, the introduction of LLMs in the qualitative research process will soon expose much more about which skills qualitative researchers value and prioritize.

Generative AI and Research Production: Moral Agency and Seductive Mediation

Gazi Islam and Michelle Greenwood
Grenoble Ecole de Management and Monash University

Imagine evaluating a doctoral thesis with the aim of judging a student's research training and capacity to engage in academic scholarship. Within the thesis, parts of the literature review may have been completed with the aid of ChatGPT or similar AI software. Similarly, the software may have helped the student to clarify arguments, to construct or format the bibliography, to suggest keywords, or to correct language errors. The program may have been used in good faith by the student. However, it may be difficult or impossible even for the student to know which parts of the argument originated from their "mind", which is working in tandem with the program along the research process. How to evaluate or judge the originality of the resulting document, or the student's capacity to engage in scholarship to the extent required to confer the doctoral degree?

Generative AI poses important questions about the ethics of research, which have generated a chorus of concerned voices joining the more general explosion of writings around Generative AI (cf., Hosseini et al, 2023). In the wake of Chat GPT's spectacular public emergence, scholars are asking themselves about the nature of writing and authorship and the ways that research practices will need to be reimagined as a result (e.g., Balmer, 2023). In our role as Editors-in-Chief of the *Journal of Business Ethics*, we are particularly concerned with the role of generative AI in the ethics of research, and as we explain in this essay, questions about the nature and extent of moral agency in research. Put briefly, evaluating the ethics of research practices requires some grasp of the kinds of moral agency at play in research, and we suspect that generative AI may affect our (often implicit) understandings of moral agency and, significantly, the very nature of moral agency writ large.

Although myriad concerns are emerging around AI and research ethics (Hosseini et al, 2023), we believe that moral agency is a particularly intractable problem because it goes to the heart of our ability to ethically evaluate practices, while being shaped by generative AI's complex relation to the human producers of content on which it is trained, and human consumers of its outputs. Moral agency, defined as the capability to deliberate and act in moral ways (cf., Watson et al, 2008), is foundational to ethical practice, as well as to the ability to evaluate ethical actors (Buchholtz & Rosenthal, 2008). Because technological developments can blur the human and non-human sources of agency (Greenwood & Wolfram Cox, 2022; Verbeek, 2011), they pose questions regarding the possibility of making ethical judgments about practices.

Following Greenwood and Wolfram Cox (2022), questions of moral agency and technology are of two separate but related orders. The first involves the visibility of human and non-human elements as sources of practice. The second involves the extent to which the means-end relations of technological mediations are visible. Both depend on a view of technological mediations as constitutive of agency (Verbeek, 2011); thus, rather than asking to what extent human agency is *substituted* by technological mediation, it takes mediation as *constitutive* of and a starting point for agency. Notwithstanding, this constitutive relation can be transparent or hidden, and when it is hidden, it can render difficult the specification of the moral agent in question, whether human or not.

Particularly pernicious, according to Greenwood and Wolfram Cox (2022) is what they term *seductive mediation*, a situation that ensues when neither the source of a communication, nor the relation of means and ends, are visible. For instance, when a text is written partially by humans and partially by machines, in ways in which these inputs are not clearly defined, the reader of the text may over-interpret the meaningfulness or human intention behind the text, failing to recognize its hybrid nature and misidentifying the functions or implications of the text. Tweets written by bots and machine-produced news stories, for example, could be interpreted as human communications, leading to misinterpretations of public opinion or of journalistic expertise, for example. In these examples, the problem is not the text itself, but the fact that it masquerades as human in ways that that make its interpretation a mine-field of hermeneutic traps.

In the context of research ethics, the human-nonhuman hybridities reflecting generative AI do not replace scholarly communication but mediate it in ways that make its claims difficult to assess. It is not just that the inputs are not clearly defined but that they cannot be clearly defined. For instance, an author's reflexive stance about their data collection experience is usually presumed by readers to reflect lived dilemmas or ongoing authorial sensemaking whose communication helps to contextualize research results. Such reflections are key to the epistemic stance of the author and the ways in which readers engage with their results. How would such engagement change if such reflections (e.g., uncertainty in coding, ethnographic anxiety, researcher-practitioner conflict) were produced by generative AI? The resulting text might have *some* kind of meaning, but it would certainly not be of the same order as if it had come from the pen of who was struggling in the field. Worse still, because at any given point it would be unknowable to readers, and indeed writers, to what extent such text was produced by humans or not, judgement around this issue would be rendered virtually impossible. It is as if such technologies render seductive mediation ubiquitous and thus obscure the sources of moral agency[7].

In such a situation, it would not be surprising if many readers began to doubt whether such text had any intelligible meaning at all, finding it safter to distrust text en masse rather than to be duped into humanizing something under the wrong premise. Alternatively, they may risk being seduced by a text whose author they (falsely) believe to be human. In either

[7] We thank Julie Wolfram Cox for this point and for overall feedback on this essay.

case, the transparency and collegial trust that provides an epistemic foundation to scholarly inquiry (e.g., Bouchard, 2016) would be put into jeopardy.

One reason that such risks could be overlooked by those promoting generative AI in research would be a presumption that the "write up" of academic results is independent of, and an afterthought to, the "research itself". Such a model of science presumes that the "true" research is done off-text, and thus that recruiting a generative AI program to help in the writing process would facilitate with a write-up that is peripheral to the core of the research process. We would disagree with such a presumption and note the wealth of scholarship that points to the importance of writing as a core part of the scholarly process (e.g., Pierre, 2015; Yore et al, 2004), both of qualitative and quantitative research traditions.

Given this question about visibility, our primary concern with generative AI is less about the substitutability of human practice with that of machines, but rather about a growing inability to specify the sources of agency in ways that make the ethicality of behavior – whether human and nonhuman – increasingly unintelligible. While moral agency is to some extent always a hybrid between human and nonhuman factors (Verbeek, 2011), the relative stability of technological mediations allows conventions to develop around how moral agency can be attributed in everyday situations. However, the deeply distributed nature of generative AI, which draws inputs from opaque sources of globally distributed data, and the rapidly evolving nature of its outputs, along with the prima facia difficulty of differentiating human from nonhuman products in this area, are likely to render such conventions difficult to establish.

In sum, we do not claim that generative AI models are anathema to ethical research practices, nor do we claim that ethical practice requires purely or primarily human inputs and outputs. However, the inability to distinguish the origin of inputs and outputs blurs the attribution of moral agency, rendering less capable our ways of understanding ethical practices and blurring the ethical evaluation of research.

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