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Generative AI, the new colleague?
– a sociomateriality perspective on the human-AI relationship

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Abstract

With the increasing human-like capabilities of generative AI, management studies have acknowledged to reconsider the traditional roles of AI, moving beyond a tool-based view towards AI as an active participant in human collaboration. Thereby, a shift towards a relational perspective when studying human-AI interaction has been recognized. This study aims to overcome the existing scarcity of empirical research on the human-generative AI relationship. Using a qualitative approach, 28 semi-structured interviews were conducted with managers in the tech field, focusing on their daily practices with generative AI. Applying the theoretical framework of sociomateriality enables an understanding of how managers and generative AI form a relationship while highlighting changing interactions within four stages of the relationship. As the interactions between managers and generative AI become more complex the collaboration within the relationship is observable, ultimately leading to interactions of a partnership. This research contributes to the field of management studies by observing the enactments of human and material practices and by identifying the transitional process from a tool perspective into a collaboration perspective in which AI becomes seen as a colleague at the final stage. Trust and solidarity remain limiting aspects of the relationship emphasizing the need for future research.

Keywords: Generative AI, Collaboration, Sociomateriality, Interaction, Managerial Practices, Human-AI Relationship, Affordances and Constraints

Introduction

The rise of generative AI compels with its humanlike responses making it almost impossible for people to distinguish a 500-word text that is created by generative AI from a human-written one (Brown et al., 2020). Beyond this simple text generation, generative AI has become a human-like discussion opponent (Korzynski et al., 2023) with its ability to create unique and creative content that mirrors human intelligence (Banh & Strobel, 2023). Thereby AI can perform both administrative and strategic tasks, entering the full range of managerial practices (Korzynski et al., 2023). This creates a new context in the research of management scholars of seeing AI as a counterpart of the daily work field of the manager (Anthony et al., 2023; Dwivedi et al., 2023; Raisch & Krakowski, 2021) calling into question the ideas of how managers work with generative AI, a technology that is much like a human itself.

Previous research on managerial interactions with AI has focused either on AI as a tool to conduct certain tasks, such as diagnosing radiology scans (Lebovitz et al., 2021), or as a medium to communicate between different positions in an organization (e.g. Bechky, 2003). Yet, recent studies have highlighted that these perspectives are no longer suitable for generative AI due to the invisibility, inscrutability, and constant change of AI (Anthony et al., 2023). Therefore, new technologies like ChatGPT should be viewed from a counterpart perspective enabling to identify AI as an active participant in interactions (Anthony et al., 2023; Bailey et al., 2022). Researchers have acknowledged the needed shift towards a more relational research approach identifying collaboration to be a suitable term for the interaction (Anthony et al., 2023; Raisch & Krakowski, 2021; Wang et al., 2023), yet few have done empirical studies on human-generative AI collaboration (Chowdhury et al., 2022). This study follows the perspective on human-AI collaboration that managers and AI co-exist but also enable one another (Chowdhury et al., 2022). At the same time, studies of AI and humans in knowledge-intense positions, have shown that the opacity of learning algorithms can hinder the adoption of AI into their work practices (Faraj et al., 2018). The black box characteristics of AI create uncertainty about how AI derives a certain output (Anthony, 2021). As a consequence trust in AI is perceived to be lower than in humans both internally by the person interacting with AI (Lebovitz et al., 2021) and externally by people observing the interaction (Kellogg et al., 2020; Waardenburg et al., 2022). Thereby studies have shown that knowledge workers substitute the work of AI by disregarding suggestions from AI and following their human judgment (Lebovitz et al., 2022; Waardenburg et al., 2022). This leads to a contrasting view in the literature where research calls for collaboration studies of generative AI, yet empirical studies on algorithmic learning demonstrate that uncertainties and mistrust can hinder the adoption of such technologies.

The lack of certainty over human-AI collaboration causes us to reconsider its nature by trying to understand the relationship in which AI and managers engage and identify whether they create a collaboration in the specific case of generative AI. Aiming to study the relationship, we draw on the concept of agency from sociomateriality as a framework that acknowledges that not only humans but also technologies can become agents of managerial practices (Floridi & Sanders, 2004). By focusing on a sociomateriality perspective, this research provides a new understanding of how managers and generative AI both can have agency in a managerial position by being constantly intertwined with one another (Leonardi,

2013a). To understand the formation of the relationship the study will follow the concept of affordance and constraint (Leonardi, 2011) and the practice lens on emergent agency (Orlikowski, 2000).

Due to the complexity of generative AI and its early stage of organizational implementation, we focus on a micro-level perspective investigating the daily actions that can shape the construction of technology on a macro-level (Leonardi, 2013a, 2013b) and close the empirical gap of generative AI in managerial practice. Managers within the tech field show strong expertise and high adaptability to new technologies making them especially suitable as study objects (Siltanen, 1993). These findings can provide a guideline for future in-depth studies of the organizational embedding of human-generative AI collaboration, guiding subsequent research that employs a zooming-in zooming-out approach to the intra-organizational enactment (Nicolini, 2009). Insights gained from this study will not only contribute to academic knowledge but also offer practical guidance for technology managers navigating the evolving landscape of generative AI, trying to overcome the practical relevance gap of academic papers (Baldridge et al., 2004). The human resemblance of generative AI calls for a new approach to human-AI interaction where a relationship is created through human and material interactions (Leonardi, 2011). The inscrutability of generative AI makes the interactions with generative AI and the manager in an organizational context unclear. Therefore, we propose the research question: How are managers and generative AI forming a relationship through interactions of everyday work practices?

The research question aims to understand the human-AI relationship by studying the interactions in the case of managers in the tech field and text-to-text generative, making us believe that qualitative studies will generate the most valuable data to study this process. We propose an initial empirical study with a thematic analysis of generative AI to provide a general real-life perspective. By pursuing a qualitative study with 28 semi-structured interviews this paper focuses on the interactions on the ground from the human perspective upon which more in-depth empirical studies can be conducted in the future.

This thesis is structured to provide a comprehensive exploration of managers' relationship with generative AI, guided by a sociomaterial perspective. Following this introduction, the thesis is organized by a literature review on generative AI, human-AI collaboration, responsibility over AI, and sociomateriality. Subsequently, we will explain the methodology thoroughly and delve into the analysis of the empirical data. Lastly, in the discussion, the research will follow a sociomateriality framework for the findings and finalize with a conclusion.

Literature review

With the rise of generative AI, the distinctions between the capabilities of managers and learning algorithm technologies become vague. Generative AI falls under the category of algorithmic learning and represents the forefront of technologies that largely mimic the cognitive abilities of humans. Algorithmic learning describes technologies that can generate responses, predictions, or classifications (Faraj et al., 2018). These tasks require technologies to understand a context and perform situational tasks by extracting knowledge from large data sets (Duan et al., 2019). Thereby algorithmic learning enters knowledge work, such as the

critical thinking of managers, that has historically been categorized as unique human domains (Faraj et al., 2018), making a clear distinction between pure human and pure technological tasks difficult.

Generative AI in managerial practices

Generative AI possesses the capacity to conduct knowledge work, characterized by its ability to create content that is novel and human-like (Banh & Strobel, 2023). This technology is primarily based on semi-supervised learning, which requires only a small amount of labeled data to facilitate ongoing learning on extensive unlabeled data (Kingma et al., 2014). Thereby it learns to create meaningful outputs from the data it is exposed to without any additional form of external supervision (Prasad Agrawal, 2023). This research focuses on text-to-text generative AI, such as ChatGPT, that can interact with the user through written language. These tools are based on an algorithm, that responds with a coherent human-like text based on predicting a response to a request of the user (Brown et al., 2020). Consequently, the underlying model can create a conversational AI tool, where the user creates a request following a text response of the AI application. These initial requests are an interaction technique called prompting, a unique generative AI property (Dang et al., 2022; Teubner et al., 2023). The user can write a short text called a prompt to engage with the algorithm and generate a text response.

Korzynski et al. (2023) identify current research trends in categorizing managerial applications of generative AI on an administrative and strategic level. On an administrative level, generative AI can be used for translation (Brown et al., 2020), answering simple questions in research (Dwivedi et al., 2023) but also to automate repetitive tasks such as scheduling appointments or writing e-mails (Korzynski et al., 2023). On a strategic level, decision-making and knowledge management can be supported through applications such as ChatGPT (Korzynski et al., 2023). The benefits in decision-making are based on providing recommendations for specific situations. These recommendations can be based on data analysis for example in the risk-management field, generative AI can evaluate companies' public financial statements and can provide an assessment of investment uncertainties (Chen et al., 2023). Additionally, interacting with AI can provide inspiration and feedback on your thought process (Dang et al., 2022; Dwivedi et al., 2023). The benefits in knowledge management are realized if the companies connect their generative AI model with their internal data system, enabling a direct search in non-public knowledge (Davenport & Alavi, 2023). The advantages of generative AI can also be found across task levels by improving learning or time management. For example, generative AI can step into the more sophisticated role of a coach to improve skill development in the management area of diverse tasks (Terblanche & Cilliers, 2020). In another example, the automation of administrative tasks can free up time for managers to focus on more creative tasks (Dwivedi et al., 2023).

By showing opportunities in managerial tasks, generative AI enters the context of managerial practices. Through their human-like performances, a new class of agents in organizations is implied (Floridi & Sanders, 2004). Recent research calls for an acknowledgment of managers and AI as being both interdependent agents of management positions (Raisch & Krakowski, 2021). Until now, AI interactions with managers have been oftentimes overlooked by management scholars (Raisch & Krakowski, 2021). However,

management studies can view human-AI interactions in real-world settings, where the technological and social worlds are merging (Orlikowski, 2010), and are therefore able to make highly needed contributions to the development of AI. In interacting with AI, managers shape and reshape algorithms and practices (Deng et al., 2017). A balanced analysis of the interactions should thereby be the focus of the study.

Human-AI collaboration in managerial practices

In the information system and management field there exist different hypotheses of how humans and AI co-exist. AI can either be viewed as a replacement for employees or a new partner for collaboration. Through studies of robotization and computerization researchers are reflecting on the potential of AI replacing humans (e.g. Czarniawska & Joerges, 2018). Whilst early-stage publications have evaluated the potential of job losses due to robotization (e.g., Ford, 2014), most recent perspectives on robotization show that jobs have not disappeared significantly since the introduction of AI (Fleming, 2019; Willcocks, 2020). Rather it is argued that low-skilled jobs proliferate while high-skilled jobs, such as those of the management, become more difficult to acquire as fewer managers are required to supervise work (Dixon et al., 2021; Fleming, 2019).

Recent studies of robotization follow the view that humans will continue to co-exist with AI (e.g. Fabri et al., 2023). The concept of how they will co-exist has been a much-debated topic within management and information systems concepts, with collaboration at the center of its research encompassing three main research perspectives.

The first perspective examines the task areas amongst which AI and humans will exist either conjointly or independently. In the context of managerial practices, tasks within this position can be either augmented or automated (Raisch & Krakowski, 2021). As elaborated before, AI can support human actors to perform both their administrative and strategic tasks within knowledge work. A strong focus has been on the ability of learning algorithms to perform repetitive and routine tasks (Frey & Osborne, 2017; Raisch & Krakowski, 2021). Whilst administrative tasks are likely to be automated, decision tasks turn into a process of augmentation, improving the decision by integrating AI into the process. The possibility of augmenting managerial capabilities through AI has been highly discussed in the field of decision-making. By working with AI, human skills can be complemented through the analytical work of AI (Brynjolfsson & Mitchell, 2017). Thereon researchers have taken the stance that the augmentation of managers can be seen as "joining forces" (Wilson & Daughtery, 2018, p.1) highlighting the collaboration between humans and AI.

The second perspective concentrates on exploring the interactions between humans and AI. Initially emerging in the 1980s, the concept of these interactions focused on humans using AI (Suchman, 2006). This focus has evolved into a newer research perspective that neglects the wording "usage". The new narrative of humans and AI develops towards a collaborating perspective, in which AI is not acted upon but becomes an individual actor of a partnership (Bankins et al., 2023; Chowdhury et al., 2022). Instead of viewing AI simply as a passive tool to be used or a medium between humans, AI is viewed as a counterpart that engages in work practices (Anthony et al., 2023). Within this collaboration managers and AI are so closely

intertwined that their actions are determined by an interpretation of the relation (Floridi & Taddeo, 2016) and not inherent in the technology (Orlikowski & Scott, 2008).

The third perspective is focused on relational studies of humans and AI. Technologies are viewed as a set of evolving relations within an organization (Bailey et al., 2022), for example a constellation of the developer, the manager and the employees (Anthony et al., 2023). Thereby relational studies on technologies oftentimes focus on the organizational context in which AI is embedded, emphasizing that the social construct influences AI's development and interaction (MacKenzie & Wajcman, 2011). The human-AI relationship is influenced by individual and organizational factors, yet individual relations with AI remain a less focused research domain (Bankins et al., 2023).

Responsibility over managerial practices

Issues of uncertainty and trust, due to the opaque nature of algorithmic learning in a managerial context, have increasingly been the discussion object of research (e.g., Wang et al., 2023). Opacity describes the opposite of transparency emphasizing the difficulty of understanding the reasons for a particular result because its derivation is unclear (Stohl et al., 2016). Although initial research argued that algorithmic learning increases confidence and reliability in AI-supported decisions, recent writings demonstrate that a lack of understanding and missing trust impede the adaptation of AI systems (Bieda, 2020; Glikson & Woolley, 2020). Various reasons contribute to the uncertainty and reduced trust in algorithmic learning. Within generative AI, data security concerns arise due to the sensibility and confidentiality of data shared in prompts with software like ChatGPT and its potential to leak data to third parties (Chen et al., 2023). Others highlight the notion of biases and their reproduction in AI-led decisions to hinder trust (Heyder et al., 2023). This is a critical factor for a relationship because difficulties in understanding generative AI oppose an obstacle to human-AI collaboration (Chowdhury et al., 2022). The research within the field broadly covers two areas.

The first area investigates the effects of algorithmic transparency on managerial acceptance of AI output (Lebovitz et al., 2022). This work is based on the reasoning that managers change their initial position based on their ability to understand the reasoning of the AI (Carlile, 2004). The uncertainty of AI results leads either to a reflective engagement with AI or an ignoration of the AI (Lebovitz et al., 2022). However, an opposing view is that managers solely rely on the generated output of AI disregarding their knowledge or capability to understand the decision (Balasubramanian et al., 2022; Murray et al., 2020). The possibility of not interacting with AI either through ignoration or blind acceptance becomes especially difficult with the purpose to study collaboration between managers and AI.

The second area investigates the distributions of accountability and responsibility over conjoint managerial practices from AI and humans (Scott & Orlikowski, 2012). Since generative AI can function on low complexity levels of routine-based tasks and high complexity levels of decision-making tasks, it can engage in the full variety of managerial practices (Korzynski et al., 2023). This creates uncertainty over the accountability of AI-based actions and questions the actor of managerial practices (Mittelstadt et al., 2016; Pakarinen & Huising, 2023). The fact that even low complexity tasks can be used as a decision basis leads to a shift from solely a human responsibility to a potentially shared responsibility of humans

and AI, leading to debates on managerial responsibility especially in decision-making (Lindebaum et al., 2020). While some researchers highlight managerial fear of making the wrong decision based on AI output (Lebovitz et al., 2021), other research shows that managers might not feel the same sense of achievement if AI has supported them (Dwivedi et al., 2023). Related questions also arise regarding the employee acceptance of conjoint manager-AI decisions as employees are unaware of the exact evaluation of their work (Kellogg et al., 2020).

The different areas indicate that a successful collaboration or even a collaboration in itself is not guaranteed between managers and algorithmic learning. Building on this notion, some research focuses on what is needed to create a collaboration (e.g. Bankins et al., 2023). Despite the challenges, research demonstrates that companies are already enhancing their managerial activities through generative AI (Dwivedi et al., 2023), thus paving the way for potential collaboration. Consequently, this study takes a step back trying to understand the relationship between AI and how responsibility is balanced across a diverse and complex task set.

Human-AI relationships within a sociomaterial framework

To understand the relationship between generative AI and managers this research focuses on the sociomaterial practices and interactions. The fact that algorithmic learning such as generative AI can possess characteristics that traditionally have been connected to human agents creates the need to discuss agential practices within the field of technologies from a new perspective (Johri, 2022). Previous research shows that sociomateriality can provide an insightful lens to study human-AI relationships (Bailey et al., 2022). It allows us to study the change in relations of emerging technologies that are inscrutable and under constant change. Yet, only a few have studied sociomaterial relations empirically (Jones, 2014).

The theory of sociomateriality has emerged as a way to see the relationship between the social and the material (Leonardi, 2013b). Highlighting the relationships, sociomaterial studies focus on the practice (Scott & Orlikowski, 2012) and interaction (Bailey et al., 2022; Barrett et al., 2012) between the social and material to understand its entwinement (Anthony et al., 2023). According to Leonardi (2013b), the social could be described as "abstract concepts such as norms, policies, communication patterns, etc," while the material could be explained as "the arrangement of an artifact's physical and/or digital materials into particular forms that endure across differences in place and time" (p. 74). By analyzing the entwinement of the social and material it can be understood how generative AI and managers form a relationship. While some research discusses potential asymmetries between the human and the AI within sociomateriality (Mutch, 2013; Suchman, 2006), other research envisions both entities as equal and simultaneously constructed (Leonardi, 2013b; Scott & Orlikowski, 2012). The latter is the focus of this research allowing for a balanced perspective on the relationship in which AI gains resemblance of a human.

According to Leonardi (2011), human and material agency are constructed by their capability to act and can only be distinguished by nuances in which human agency concerns how people have the capacity to achieve their goals, while material agency concerns how technology does specific aspects that the people are not entirely in control over. Consequently, people need to accept and work around the material agency in order to reach their goals (Leonardi, 2011). Agency does not only need to be understood as something that humans obtain

but also in relation to materiality. Due to the perceptual element of technology, technologies are not to be seen as independent and definite as materiality is able to gain agency and capable of both being acted upon and be acting (Styre, 2017). The perceived ability of the technology to enable the person interacting with it to achieve their goals does also affect the material agency. In other words, the perceived affordances or constraints of the person interacting with the technology together with the materiality itself, constitutes the way technology is acting and being acted upon (Leonardi, 2013b). As stated by Orlikowski and Scott (2008), work practices are constituted not only of social practices but also of materiality, and sociomaterial practices are not able to be reduced to solely the technology itself or the social aspects. Leonardi (2011) further explains how the affordances and constraints can appear in the relationship between people and materiality, as people perceive whether the technology can help them accomplish their goals or not. Observing the affordances and constraints that are related to the materiality of the technology is beneficial when aiming to understand how the social and material practices are being shaped (Leonardi, 2013b). Depending on these perceptions regarding affordances and constraints, new intentions can be realized that could be accomplished through the material features which consequently might end up in new routines (Leonardi, 2011).

Although the concept of affordances and constraints have found high resonance in empirical studies (Cranefield et al., 2022), it shows difficulties in presenting the entanglement between humans and technology within a relationship (Faraj & Azad, 2012). This is because, within empirical research, the material would need to be at least implicitly defined, which would decouple the material from the social and contradict the constitutively entangled stance in sociomateriality (Leonardi, 2013b). An attempt to overcome these issues appears in a study on the opacity of AI that considers sociomateriality as enacted in practices rather than treating characteristics of AI as inherently possessed (Lebovitz et al, 2022). This is described as constitutive entanglement, meaning that there are entities that only exist dependently without inherent characteristics (Orlikowski, 2007). Consequently, the choice is made to define the characteristics of AI through sociomaterial practices and follow a more nuanced perspective on relations (Faraj & Azad, 2012). Therefore, viewing the relationship as mutually constitutive from the beginning could lead to the researcher overlooking how the relationship is being shaped just as well as the reasons behind it (Scott & Orlikowski, 2014).

Building upon Orlikowski (2007), in this thesis the material and the social are seen as mutually shaping one another yet not independently existing individuals. The relationship between the social and the material is constituted through each other's interactions (Scott & Orlikowski, 2014). This makes us understand agency as something that is created within the relationship of generative AI and the manager. Through the interactions of AI with humans, the agency is identified in relationships created through non-human and human practices (Fabri et al., 2023; Latour, 1987). The theoretical perspective of sociomateriality supports the study by providing a lens that makes us view interactions equally shaped by the manager and generative AI. Sociomateriality as a framework sees the agential relationship as a whole and not a framework for human and technology-separated (Cecez-Kecmanovic et al., 2014). Thereby the material and the social are seen as one entity while the agency is not located in technology or humans but rather lies in the intra-actions of the sociomaterial (Orlikowski, 1992).

Building upon the theoretical framework of sociomateriality when understanding how materiality is an integral part of everyday work practices, the concept of agency supports the observation of the relationship between managers and generative AI (Orlikowski, 2000). As stated by Barad (2007): "It is important to note that the 'distinct' agencies are only distinct in a relational, not an absolute sense (…) they don't exist as individual elements" (p. 33). Furthermore, agency is not a concept that someone has inherently but instead comes out of sociomaterial enactments (Orlikowski, 2010). Moreover, the iterative process of performing social practices and work routines requires an understanding based on what Orlikowski and Scott (2008) call sociomaterial reconfigurations in order to perform organizational realities. The continuous reconfiguration of the sociomaterial work practices, referred to as practice lens, is therefore what constitutes agencies and not inherent attributes of humans or technologies. Applying a practice lens is beneficial due to the performative element being central in sociomateriality and the relationship between humans and technology is not pre-determined but instead understood through the enactments of technologies in practices (Orlikowski, 2000). According to Scott and Orlikowski (2013) a theoretical plurality in studies should be maintained to allow for new perspectives and experimentations. Thereby the framework of this study combines the complementing studies from Leonardi (2011) on affordances and constraints and the practice lens on emergent agency of Orlikowski (2000).

Methodology

As outlined by Silverman (2022) qualitative research is especially suitable for being able to analyze the in-between, how situations evolve, and how people communicate. In an attempt to study the AI-managerial relationship, we pursued qualitative research through interviews and gained access to managers with experience in daily interactions with AI. Focusing on managers across different organizations enabled us to gain a larger data set of the individual activities of managers and AI, exceeding the number of managers in one organization. This cross-organizational study allowed us to focus on the relationship rather than the social embedding and surroundings that constitute the context shaping sociomaterial practices (Scott & Orlikowski, 2012). Thereby we observed relational practices between managers and AI, instead of organizational practices, highlighting the formation of a relationship. Each manager engaged in a relationship with generative AI which was differently formed and shaped on an individual level and which could be aggregated across the interviewees into the evolving process of a relationship.

The research followed a micro perspective (Leonardi, 2013b) by focusing on the daily practices of managers and generative AI that shape a relationship. Analyzing micro-actions, such as managerial practices, rather than macro-level patterns has proven to be a suitable method for relational studies by showing variations in the enactment of social and material entanglement as something processual instead of stable (Jones, 2014). The thematic analysis of the collected data focused on relational practices enabled us to understand both the manager's and generative AI's engagement. Thereby we could explore the dynamic and co-constitutive nature of social relations and material artifacts highlighting the interplay between social and material elements (Orlikowski & Scott, 2008).

Setting of the study

To understand the relational entanglement of managers and generative AI we conducted 28 semi-structured interviews of managers in the tech field (see Table 1). The managers were selected based on responding positive to using text-to-text generative AI within their daily work practices through a request via companies' open inquiry e-mail addresses. Due to the similar user interface, ChatGPT and Microsoft Copilot could be utilized. The managerial positions had to incorporate both administrative and strategic tasks such as Chief Product Officer or Head of Digital Innovation. This allowed us to observe interactions with AI across all potential task application levels. Given the preliminary stage of this generative AI study and the fact that few managers currently employ generative AI (KPMG, 2023), we wanted to ensure that the interviewees had sufficient expertise and experience in interacting with generative AI to potentially be entangled in a relationship. Research has proven that employees with intermediate expertise in technologies, such as managers in the tech field, are usually more prone to use AI and identify its benefits (Allen & Choudhury, 2022). Moreover, the work context, such as transport, medicine, etc. is crucial for people's willingness to interact with AI (Schwesig et al., 2023). Therefore, focusing on a technical work context among the interviewees supported the acceptance rate of generative AI and ensured a high willingness to interact with AI.

The managerial tech field focus was ensured by interviewing managers who either have a managerial position focused on technologies or who work in a technology-related company. Managers with a technology-focused position have responsibility over technologies whether it is the programming process, the technical products, or technology implementations. This can be found in positions such as Manager for Digitalization or Lead Data Scientist. Contrary, managers within a technology company contribute to the production of technical products. A technical product can range from software development to IT service providers. Their managerial responsibility does not necessarily have to be tech-related and can include various departments, or projects, such as a Director of Marketing & Sales. Nevertheless, the position can directly be linked to the technical product such as Chief Product Officer. Studying both these two types of managers enabled a large set of data consisting of interviews with 24 male and 4 female managers within the tech field.

In the following sections, both types of managers within the tech field are collectively referred to as tech managers. Although their work practices showed differences, we could identify administrative and strategic tasks that create a similar interaction potential with AI. The daily work of both manager types in the tech field consisted of writing company updates, reading articles, participating in meetings, and negotiating with different stakeholders. Work practices of a manager in a tech position included additional evaluations on software investments and policies, as well as occasional coding whilst managers in a tech company evaluated product developments, developed organizational strategies, and connected with clients.

No.	Gender	Tech Focus	Position	Country	Application
1	Male	Company	Chief Product Officer	Germany	ChatGPT
2	Male	Company	Chief Product Officer	Germany	ChatGPT
3	Female	Manager	Manager of Digitalization	Sweden	ChatGPT / Copilot
4	Male	Manager	Product Owner	Sweden	ChatGPT / Copilot
5	Male	Company	Manager for Strategy	Sweden	Copilot
6	Female	Manager	Head of Digital & Innovation	Sweden	ChatGPT
7	Male	Company	Senior Manager	Sweden	ChatGPT
8	Male	Manager	Head of AI Governance	Sweden	ChatGPT / Copilot
9	Male	Manager	Lead Data Scientist	Sweden	ChatGPT / Copilot
10	Male	Company	Director Marketing & Sales	Sweden	ChatGPT
11	Male	Company	Senior Manager	Sweden	ChatGPT
12	Male	Company	Chief Product Officer	Sweden	ChatGPT
13	Male	Company	Lead Data Scientist	Sweden	ChatGPT / Copilot
14	Male	Manager	Manager of Digitalization	Sweden	ChatGPT
15	Male	Company	Chief Product Officer	Germany	ChatGPT
16	Male	Company	Chief Executive Officer	Sweden	ChatGPT / Copilot
17	Male	Manager	Manager of Digitalization	Sweden	ChatGPT
18	Male	Company	Chief Executive Officer	Sweden	Copilot
19	Male	Company	Product Owner	Germany	ChatGPT
20	Male	Manager	Chief Technology Officer	Sweden	ChatGPT
21	Male	Manager	Lead Data Scientist	Sweden	ChatGPT
22	Male	Company	Head of Development	Sweden	ChatGPT
23	Male	Company	Chief Executive Officer	Sweden	ChatGPT
24	Male	Company	Chief Executive Officer	Sweden	ChatGPT
25	Female	Company	Lead Customer Care	Sweden	ChatGPT
26	Male	Manager	Senior Manager Digital	Germany	ChatGPT
27	Female	Company	Manager for Strategy	Sweden	ChatGPT
28	Male	Manager	Manager of Digitalization	Germany	Copilot

Table 1. Characteristics of interviewed managers in the tech field

The participants were based in Sweden and Germany, to leverage the advanced AI integration in these countries' tech industries. According to Hofstede Insights (2023), both cultures show a pragmatic orientation towards changes making them capable of adapting easily to the emergence of new technologies. While acknowledging that organizational cultures may differ, this study focuses on the relational dynamics with AI across similar managerial roles.

Therefore, the potential variability in organizational culture is not a primary concern for this research, as the emphasis is on understanding the interaction between managers and AI technologies, which transcends local cultural specifics.

Data collection method

By following a semi-structured interview, the managers in the tech field were able to speak freely about their own perceptions and ways in which they interacted with AI (Bryman & Bell, 2011; Silverman, 2022). To gain an understanding reduced in preconceptions we followed a grounded approach with the interviews (Anthony et al., 2023). In alignment with Charmaz's (1995) understanding of grounded studies, we developed our interview guide through initial broad questions allowing for open data collection, such as "How do you integrate generative AI in your daily work life?". This allowed us to identify more prominent topics and narratives that were brought up by the interviewees themselves and identify similarities across different managers. Moreover, the broader perspective of the questionnaire and managers across multiple organizations enabled us to ensure the transferability and applicability of our findings (Carminati, 2018).

To provide an open atmosphere, the interviewees could choose the language they felt most comfortable with (Chen, 2011), resulting in conducting the interviews in the manager's respective first languages. In the initial interview, both researchers were present to ensure consistency in the interview style. Subsequent interviews were conducted individually to mitigate the power dynamics of the interviewer (Kvale, 2006). The interviews were conducted online, via Microsoft Teams, to overcome physical distance in a cost-effective and easy-to-use way, while being aware of the risk of technical problems (Archibald et al., 2019). The majority of the interviewees were already familiar with Microsoft Teams within their organization, leading to almost no technical problems. The duration of the interviews ranged from 32 minutes to 71 minutes. Through an iterative data collection and data analysis process, we could identify data saturation at 28 interviews (Bowen, 2008; Glaser & Strauss, 1967).

Data analysis

The interviews were recorded and transcribed by the interviewer. The transcription was automated through Microsoft Word Online and then examined by the researcher while simultaneously listening to the recorded audio file. Thereby, not only errors could be detected but also previously unnoted features, reoccurring wordings and underlying meanings of the managers on the relationship (Silverman, 2022). The interviews were then translated by deepL and discussed with the other researcher to overcome misinterpretations of wordings (Winchatz, 2006).

To identify themes of managers' relationship with AI, without being influenced by the strong public narrative of AI (Anthony et al., 2023), we perused an open coding approach where no codes were initially generated but derived from the empirical data (Corbin & Strauss, 2008). The coding process was conducted on NVivo to facilitate a collaborative qualitative data analysis. The initial phase of the coding process was to identify important codes related to the relationship between managers and generative AI. By coding meanings instead of sentences or words, we could overcome the decontextualization of the responses (Garrison et al., 2006).

Since two researchers have conducted this study, securing intercoder reliability was an important issue (Campbell et al., 2013). To ensure intercoder reliability we followed the guidelines of Campbell et al. (2013) and each interviewer initially coded the first interviews individually and compared them to agree on the codes and coding approach. To strengthen reliability, a codebook was developed following the coding of the first set of transcripts together, including codes that were well-defined and commonly understood by the researchers. The codebook supported getting an overview of all of the codes as well as enabled both researchers to track where every single code stemmed from within each of the transcripts (Campbell et al., 2013). The following interviews were coded separately. The additional codes that were derived during the coding process were collectively discussed and subsequently incorporated into the codebook. After our initial study of the data, we refined the coding scheme and sorted the codes topic-related into axial coding groups (Corbin & Strauss, 2008). Generating overarching themes out of codes was beneficial to understanding the codes more thoroughly (Braun & Clarke, 2006).

1st Order Concept	2nd Order Themes	Aggregated Dimension
Routine based tasks Time-demanding tasks Inspiration	AI is performing tasks	Support
More time for strategic tasks More time spent with partners More time to increase work quality	Managers can do more tasks	
Creating data access Third party information Private information Strategic company information	AI gains data availability	Hesitation
Adaptation of practices Unclear usage Time-consuming prompting	Managers change work habits	
Confirmation on uncertain topics	AI gives personal reassurance	Validation
Potential of wrong results from AI Sensibility for hallucination Sensibility for ethics Controlling sources	Managers fact check	
The manager is responsible for the used results	AI questions responsibility of work	
Rewriting generative AI results Ensuring copyrights Appreciation of effort	Managers personalize	
Responsive discussion Easy user interface Providing context of the manager and AI	AI communicates human-like	Partnership
Nicknames Approaching AI instead of colleagues Unimaginable to be without AI	Managers replace human interactions with AI	
Low understanding of context Missing initiative for follow-up question	AI is no full human-being	
Presenting the results to humans Adding human experience	Managers seek group cohesion	

Table 2. Thematic analysis of interactions following the Gioia method (2013)

The data analysis of this study was conducted through the thematic analysis provided by Gioia (2021), which comprised three steps. Firstly, the open codes generated during the initial coding were sorted into categories with the objective of creating first-order concepts. The initial aim was to maintain a substantial number of categories for the researcher to subsequently identify and delineate the key categories. The second step was the creation of second-order themes, where the first-order concepts were reviewed from a theoretical standpoint. Thereby we followed Gioia's (2021) key question: "Can I see something the informants themselves do not see?" (p. 25). Aiming to study the relationship of managers and AI we identified practices from the manager and AI that formed the relationship, such as "AI is performing tasks" (see Table 2). By going over the concepts with more of a theoretical perspective in mind, the key categories that alluded to a similar topic were structured under the same theme. The last step was that of creating aggregated dimensions, where the second-order themes are distilled even further from a theory-centric point of view. Concerning this step, four major aggregated dimensions were created based on the interactions between managers and AI that are created out of the practices. This method permitted the presentation of the data in an overview of concepts, themes, and aggregated dimensions as presented in Table 2 above.

Limitations and Ethical Reflections

The data collected in this study was anonymized and handled following the privacy regulations of the University of Gothenburg (2023). The participants were informed about the process as well as the purpose of the study and their role in it, aiming to reduce their risk of withholding information. Moreover, all interviewees were informed of the measures taken to ensure the confidentiality of their data and could withdraw their participation and request the cessation of recording at any point.

Reflecting on our method from an ethical perspective, we need to acknowledge that this study has been conducted by two researchers of different sexes. Although we aimed to align our interview style there is an inhabited difference in conducting interviews by male or female that might have affected the responses of the interviewees (Matteson & Lincoln, 2009).

The methodological limitations of our study are primarily based on the setting. While the study selected managers with experience in technologies, it is primarily limited to those who responded positively about their AI usage. This could create a selection bias, as it may exclude those who no longer interact with AI based on negative experiences and limit the transferability to all tech managers (Clougherty et al., 2016). Moreover, the interviewees could identify generative AI as taken for granted meaning that they will struggle to articulate how they interact with it (Orlikowski, 2000), reducing the accuracy of the interviews. However, due to the novelty of text-based generative AI, we believe that the taken-for-granted perspective is still limited. Furthermore, despite aiming for transferable findings and focusing on practices with AI, interviewing managers of different positions can remove the contextuality thus our findings need to account for that.

Empirical findings

The focus of the analysis is to understand the relationship between the manager and generative AI and how they engage in it. The aggregated dimensions, described subsequently, are individual parts of the process of forming a relationship (see Table 2). They are presented below in the initial order of forming a relationship: First, the interest in a relationship is created due to a supporting function; second, a hesitation is opposed due to accommodating activities; third, mutual validation is shaping the work of the relationship; and fourth, managers and AI engage in a human-like partnership. Nevertheless, it is not always the case that these dimensions are sequential, they can also be iteratively and only partially exerted. Each process step can influence another through interacting in the combined process of a relationship, without necessarily following each dimension. In the following section tech managers will be referred to as M with their respective numbers. Their detailed characteristics can be found in Table 1.

Dimension of support

The manager and generative AI engage in a supporting function through their interactions. Managers can identify the benefits of gaining support in their daily work life and based on that decide to engage in a relationship. The support that is gained through the interaction of managers and generative AI is based on two aspects.

The first aspect is that generative AI can perform certain tasks in the managerial position. Many tech managers describe how ChatGPT and other applications can provide support in routine-based tasks such as structuring e-mails, rephrasing LinkedIn posts, or translating messages and technical manuals in an international work context. By creating text content with AI, managers can improve their writing styles. Whilst some managers explain that they provide AI simply with their notes and ideas others already have a pre-written text and expect AI to rewrite it. Thereby the tech managers highlight the improved grammar, text structure, and word variety. Those that emphasize the text quality increase, highlight that formulations are one of their weaknesses. One manager asserts that their writing style oftentimes reflects the inner thought process making it difficult for others to understand, but through AI the clarity and coherence improved significantly. Furthermore, those managers who do not feel comfortable with a second language show strong interest in ChatGPT's business vocabulary and formulations. One interviewee describes AI's routine-based supporting role as:

> [It can] respond, summarize documents and everything like that which we otherwise do manually, and even with translations we have previously done manually. Some assistant or some junior lawyer has had to sit and translate contracts manually from page A to B and now of course you use these tools with the features and you get a translation - M6

Additionally, time-demanding tasks that are described as "not great fun" (M16) can also be supported by generative AI. These tasks can range from finding an important Excel file, that the manager knows exists but not where, to summarizing company statements, meeting notes, or e-mails that otherwise take a long time to read and understand. The summaries generated with AI appeal to the managers due to the low time requirements and the clear structure. For example, it can extract the root cause and solution of a long e-mail threat that managers receive

and would have worked through manually before. In addition to the summary, tech managers can ask questions about the provided documents or e-mails so that they no longer have to scan the whole file but can quickly read the important section, like a "little intelligent FAQ" (M12).

Moreover, generative AI supports the inspiration process of managers. Instead of starting on a blank page, AI generates ideas and creates that first draft – "you do not need to start with an empty canvas" (M8). This draft is the support the manager needs to further develop PowerPoints, e-mails, or LinkedIn posts by skipping the time-consuming initial phase of idea generation. The draft creation usually contains two steps. First, there is an initial phase of understanding a topic which is often an individual thought process and has been supported by search engines in the past. Unlike other technologies such as Google, ChatGPT can combine multiple sources reducing the time managers would have to spend on screening multiple articles provided by Google. One interviewee explains the difference like this:

> In Google you only get lots of examples and then you have to sit and read and it takes so long to read all this. Whereas on ChatGPT I get a summary view of it anyway. Then I kind of do not have to read through four articles or five articles to get a summary – M13

Second, generative AI can support the actual idea generation and draft creation. The topics managers want inspiration on can significantly vary such as workshop invitations, information on security measures, or writing a contract. The questions managers then ask are content-based such as: "How could I conduct such a workshop? How could I structure it? What points should I have in the invitation?" (M11). Thereby applications like ChatGPT provide an overview and creative suggestions on the topic. Leveraging these ideas, managers can skip their initial brainstorming phase and further develop AI's ideas based on whether they like, dislike it, or identify missing aspects in AI's list. The process of understanding a topic with its potential breadth and depth is described as highly shortened due to the support of AI.

The second aspect of support shows in the analytical parts of a manager's daily work that generative AI cannot help them with but indirectly supports them by providing more time for it. The support from AI is recognized as time efficient as it enables an acceleration of routine-based, time-demanding, and inspirational tasks. Therefore, tech managers "can do more in the same time" (M2). The areas in which the managers use their additional time can vary. Some report that they spend more time on strategic tasks and others state that they spend more time creating analytical output for customers instead of being stuck on repetitive tasks. One manager describes the synergies between AI's support and the manager's own work as such:

> I can become more effective as a leader to spend less time on routine tasks, be more present in the organization, be closer to the people by getting that support and that assistance - M17

The strategic tasks are seen by the manager as "fun" (M17) as they are significant for the company's success and require their managerial expertise. One interviewee summarizes the time synergies with AI as such: "It probably saves me half an hour every time, which allows me to focus on what actually requires the human brain in a different way" (M27). Both strategic and analytical tasks are viewed as more valued by the interviewees since AI cannot conduct them. Moreover, the acceleration of simple tasks shows an increased speed in managerial decision-making as managers reach the point of option evaluation more quickly. Furthermore,

many highlight how the work content quality has increased resulting from having more time to investigate details, gain a broader perspective on the topic and develop ideas more thoroughly. One manager called this effect "a performance booster" (M8).

Additionally, the time-efficiency is used by managers to spend more time with clients, partners, or colleagues. Due to e-mails being generated faster and simple questions being quickly answered by AI, managers spend less time planning and more time with human interactions to discuss complex topics. Those soft values are summarized by one interviewee as "[having] more time to spend on personal conversations with people or just walk around the office landscape" (M27). Thereby, managers feel that they can use their time more effectively. A direct synergy between AI and the managers' attendance in the physical world is identified by one manager. The manager describes that generative AI could provide a summary for a large part of meetings that they currently attend yet often feel unnecessary:

> It will be fewer people in meetings and then a summary goes out that the AI has generated; 'this was what was being said during the meeting, these are the key points, these were the tasks that were delivered'. … instead of that people have to spend time in meetings that could have been an e-mail, you just receive your summary – M8

It is even possible to identify a non-productive benefit of a manager getting coffee while ChatGPT is solving a prompt: "I'll do something different at that moment. Get myself a coffee or prepare the website for a colleague" (M2). The tasks AI can do and those that the manager can do more in-depth both show how the relationship between both parties consists of support.

Dimension of hesitation

Although managers and AI engage in a supporting manner it can also be noticed that hesitation is shaping their relationship. To create the relationship preconditions for the managers and the generative AI applications need to be met that can oppose hesitation.

First, the manager needs to change its existing work habits so that applications like ChatGPT can be integrated. This step consists of a continuous adaptation and learning process. Although many interviewees explain how interacting with generative AI is straightforward, they still admit that their working habits have to be changed. These habits can be rather simple as in switching from Google to ChatGPT or can be more complex as in understanding how ChatGPT structures its output. One manager explains:

> It's still a bit like this with the power of habit, so it's very easy to, you know, google a question or google when gathering information. But then I've also started to realize that I can ask the question to the chat, but so far I can say I'd rather google questions because it just feels like it's a habit – M7

The time this adaptation process takes can vary, however, tech managers highlight that it not only takes time, but they have to actively make time to foster adaptation and learning. Managers need to acknowledge the potential support an interaction with AI will provide and then spend time to familiarize themselves with AI by understanding the underlying mechanisms, the interaction techniques called prompting, and the possibilities to extract the most benefits from interacting. To engage in a relationship, managers need to spare time to gain knowledge and

change their work practices. This trade-off between time and benefits from the support is elaborated by a tech manager:

> Time is money in this industry. We sell time and everyone is always under pressure to work a lot on weekends, evenings, nights and then to take the time to kind of stop and 'no, but now I'm going to do this in a new way', it's always like a threshold before you are up and running with something new – M6

Both interest and age are identified as key determinants of the adaptation and learning process. The majority of the interviewees share their perspectives on the early stage of adaptation. Many interviewees employ similar phrases like "But it is also, again, very early at the stage" (M5). Generative AI has recently been introduced into their work practices. Consequently, the interactions are still explorative and mainly driven by their interest in technologies. The novelty of the new AI technique leads to uncertainties in adaptation. Some report that understanding how AI works is difficult while others underline the missing guidelines on how to benefit from generative AI the most. In some cases, the adaptation to ChatGPT or Copilot is discontinued due to the manager's belief that the tasks can be done faster or better themselves. One manager describes the uncertainties as managing a jungle of AI: "Which applications and which models are good and what suits us and navigate the jungle because right now it's a jungle" (M11).

Furthermore, a strong difficulty in the relationship between managers and generative AI is the unique prompting process that does not exist with other AI algorithms. Managers describe the prompting process as iterative. The first results from ChatGPT etc. are mostly not used, but new, more specific prompts are created thereafter to refine the results:

> You rarely get the perfect answer the first time, so then it's important to ask a follow-up question and ask for clarifications and improvements to the answer of course, so that with one, two or three iterations you can usually get a pretty good answer – M17

While this iterative process is described by many interviewees, some believe that their formulation of prompts was the cause of the problem of vague results. Consequently, prompting has been identified as time-consuming, and in some cases, managers give up on the iterative process due to time constraints or dissatisfaction with the quality: "I have also had cases where I gave up because it took too much time for me to ask and formulate things over and over again. And it's not fast either" (M2).

As a second precondition of the interaction, generative AI has to gain access to information and data. On the one hand, managers provide AI with information in the prompt formulation on their customer, company and personality thus enabling AI to generate insightful results. On the other hand, it can be beneficial if technologies like ChatGPT have direct access to internal documents of the organization, providing internal sources for AI. While interacting with the manager, AI necessarily gains availability on some data. However, many of the interviewees indicate hesitation in revealing information. Generative AI is perceived as an external server making every data available to AI a potential obstacle for security. One manager described the external server: "You do not know where the information is processed and ends up" (M22). Consequently, tech managers discuss data security on an external, internal and private level. The interviewees agree that external, third-party data, such as those from clients

have to be anonymized as the managers have no rights on them. The opinions on company internal data are torn between the managers. Some argue that technologies such as ChatGPT along with their developers are incapable of accessing the strategic data that will be revealed in a prompt. Other managers view ChatGPT and Copilot as full external actors and restrict the usage for strategic and company internal content to limit the risk of exposure. This can be observed in the following exclamation:

> ChatGPT is an external service and has to be managed like that. I can't explain that 'I'm a manager that works at *company name* and do all of these things', that leaves too much information to the AI that is too detailed simply put - M8

By reducing AI's data availability managers notice that the interaction capabilities are limited and inspiration in complex contexts is not possible. Especially, strategic projects that have not been open to the public are oftentimes made unavailable to AI. Although managers interact with generative AI, in some cases they prevent AI from some data availability. One manager describes their way of avoiding company internal data access as: "We write the press release in Word beforehand not using any generative AI" (M16).

Moreover, managers also fear to reveal private information about themselves. Despite recognizing the need to reveal certain private information, like position or personal preferences, they highlight that it is a strange feeling to tell AI about themselves and they will not reveal everything. At the same time, they acknowledge that due to registrations of the residence and websites like Facebook, there is already a lot of information on the managers online. Still, they explain the step of giving AI personal data: "It's more a bit scary the first time you do it" (M8). To engage in the relationship on the one hand managers need to accommodate their existing work practices to incorporate AI and on the other hand generative AI needs to have access to information to provide precise results. Although managers are aware of the prerequisites that need to be met for the relationship, they still hesitate to reveal information and learn about the usage of AI.

Dimension of validation

Even when hesitations on the relationship are overcome, one can identify a consistent step of validation. This validation in the relationship comes from both the manager and the generative AI. On the one hand, generative AI provides a source of validation for the manager. By double checking if ChatGPT would have given them a similar approach to a problem, managers gain assurance especially when either the topic or the task is new to them. One interviewee even describes that if something is created without interacting with generative AI, the manager is doubting the quality of the work. Another manager highlights the capability of AI to not only reassure but also identify overlooked areas of the work:

> I think idea generation is good (…) as a completion check. If I have a topic, it can tell me what else there is. For me, this is a great check to see whether I'm mutually exclusive and have covered everything. – M26

On the other hand, managers feel obliged to validate AI generated content. This is a consequence of tech managers noticing that AI can make mistakes: "When you start writing specific things, it can become very wrong and then you have to know that" (M8). Therefore,

applications like ChatGPT call into question who is actually responsible for the final output of the work that is created within the relationship between tech managers and generative AI: The generative AI? The developers of AI? The manager? The responsibility is frequently discussed among the managers. Concluding, they agree on viewing themselves as responsible for the generative AI both for the data included in the prompting and the quality of the result. One interviewee compares ChatGPT with a knowledgeable person who supports in daily tasks but for whom the manager is responsible.

The responsibility of the manager over AI is exerted by including fact-checking as a practice of the relationship. Managers oversee whether the answers of generative AI are relevant and double-check sources provided by AI for correctness. This is motivated by their preliminary assumption that answers from generative AI could be wrong:

> But my point of departure is always that they [AI] are not right. It has to do with the fact that the language model is such that even though it may be right in substance, I may not think that it is right. (…) So I always assume that it could be flawed and I've noticed that it is a lot – M24

Not only are the managers critical about the correctness of generative AI but they are also sensible about ethics and potential hallucinations. Ethical sensibility is caused by potential biases of generative AI results. Some managers discuss the possibility of biased results of generative AI that can potentially be negatively abused – "for evil intentions" (M27). Another one adds that only a few developers are in control of the results of ChatGPT etc and can alternate the truth. Moreover, interviewees highlight the caution of unselected sources that AI draws from. One manager underlines that if one opinion is highly represented on the internet it will also replicate in AI's content. These concerns of ethics and abuse make the interactions not fully reliable and highlight the importance for the manager to reflect on AI content. Concluding, one manager says: "I will always endeavor to avoid extreme viewpoints and positions" (M15). Concerns about hallucinations are more focused on ChatGPT creating information that does not exist. Therefore, the interviewees are alerted when noticing "What kind of strange thing does (AI) write?" (M6) and rewrite responses to ensure credibility. However, the managers need to have a certain understanding of the topic to identify incorrect statements from generative AI. If the managers' knowledge of the area is too limited, they either do not interact with AI or they ask other people to proofread. One interviewee explains that they have to consult an expert on the topic to identify the mistakes AI has made.

Apart from fact-checking managers identify personalization as an important step in the interactions. Despite AI being able to generate texts that support the managers, many report that the texts are missing personality and the responses are rather general.

> Often it is that it sounds far too formal. It simply sounds too good. 'But my colleague didn't write that. (…) I've never seen him write like that. But now, all of a sudden, he writes very correctly and formally' – M11

Consequently, managers only take the ideas from generative AI and rewrite them afterwards. This rewriting process is motivated by three reasons. First, they want to make it sound personal and more human-like, believing that texts generated from AI are identifiable. This can be summarized by: "I kind of just write so that I feel like I'm the one who sent it." (M24). Second,

they want to avoid the label "generated by AI". Either because it might be perceived negatively by others or because it might reproduce content that is protected under copyrights. Third, they believe that rewriting texts from generative AI represents the appreciation of the task. Changing the phrasings or even the content of ChatGPT and Copilot shows that the task is important and valued. The opposite, if it has not been changed, shows "laziness" (M24) or that "it's not worth it" (M2). The interviewed managers describe that they are not proud of writing texts with AI and others have a lower interest in reading texts generated by AI. Both aspects of fact-checking and personalization can be based on the fear of letting generative AI act on its own, being mentioned multiple times. The autonomous actions of generative AI is described as "the point [where] you lose control" (M7) and "a nightmare" (M8). Validation is a significant step in the relationship, for reassurance on the one side but on the other side to highlight the responsibility of the manager through fact-checking and personalization.

Dimension of partnership

The relationship between managers and generative AI is identified through actions of partnering. The partnership is embodied in the communication between managers and generative AI having both internal and external effects.

First, generative AI and managers communicate internally in a human-like manner. The interactions resemble those of a colleague: "How you ask questions and which questions you ask is probably just like the dialogue with colleagues at work" (M14). The discussions are described as responsive and interactive. Instead of gaining generic answers, the managers can provide context both about themselves and about AI. Through details on the manager's preferences and work situation AI becomes aware of the environment of the manager and can tailor the output accordingly. Additionally, managers choose which position ChatGPT or Copilot should fill and how it should behave. This enables the manager to choose the discussion opponent, such as "from now on, act as you are a compliance officer" (M4) and due to the context provided the communication is filled with background information and responses that are based on individual knowledge, making it feel like one is talking to a human. One manager describes this process as "being a good storyteller just as for humans" (M4). The sharing of context is perceived to enhance the quality of the results. Consequently, they aim to have an individual chat for each context within the application, so that AI can remember like a human, and they avoid starting over each time.

The interface of text-based generative AI allows managers to have a responsive interaction and they cite that they are having "discussions" (M3) and "conversations" (M2) with generative AI. Due to the chat field within the applications, it is not only referred to as easy to interact with, but managers also start engaging in an interactive conversation with AI. This interaction is shaped by recursive back-and-forth questions with AI. Thereby generative AI is referred to either as a "dialogue partner" (M10) or a "professional discussion partner" (M12). Within this dialogue, managers incorporate filling words like "I need a …" (M19) and curtesy words like "thank you" (M12) making it sound like human conversations. One manager summarizes it by saying: "It's tempting to talk to the thing like a person. It's more comfortable

and it's easier to think" (M19). Another interviewee fears that discourteous communication with AI would transfer into the external world and chooses to remain polite with AI:

> When you start to be careless with politeness or anything like that, you will start to be careless in context with real people as well, so I try to keep it with both greetings and thanks – M14

Moreover, managers compare the characteristics of AI with those of a human. Thereby hallucination is seen as an obstacle, but at the same time something that all humans do. The following interactions between managers and AI are compared to either verbalizing an internal thought process or to a discussion within a team. One manager highlights: "The process is very similar to working with someone else" (M1). In particular, those within managerial roles are aware that their workday consists of many external meetings making their internal meeting times limited. Consequently, managers appreciate the opportunity to engage in dialogue with AI, rather than being left isolated at the end of the day: "I use it because I don't have a colleague to ask or collaborate with" (M12).

Second, the external effects of communication between managers and AI can be identified by changes in human communication. On the one hand, managers replace human interactions with generative AI. Many interviewees report that in some situations they approach AI instead of their colleagues. Some do not want to disturb their human colleagues while others appreciate the anonymity of generative AI to discuss sensitive topics. One interviewee recounts how a colleague had experienced the death of a family member and was uncertain about the most appropriate means of providing support. Consequently, the manager seeks anonymity of AI to pose the following question:

> 'How do you support someone when you know they're having a little bit of trouble privately without intruding?' These are things that typically take a lot of time for me to find the right words. – M3

Other managers highlight the constant availability and unlimited time capacity of AI, making it appealing to approach AI instead of colleagues. Consequently, one manager explains the benefit of never disturbing AI: "Otherwise I would have to abuse those around me. For this ping pong, for sharpening your thoughts" (M2). Another manager draws attention to the fact that the colleagues do not have the same availability on the weekend as AI does:

> My communicator, she usually helps me write the CEO's speech, and often we sit and spend a while together (…). So you take a few turns before it's ready. This time, it almost happened instantaneously via AI on a Saturday and she didn't have to come in on the weekend and write this – M18

Moreover, department-specific but rather simple questions that would have been answered by colleagues of the IT or Research and Development departments, among others, are answered quicker by AI and do not disrupt anyone's workflow: "It can explain a lot of obvious things in their [colleagues] world to me then" (M14). On the other hand, the interactions with AI influence the communication style between humans. The managers report how they believe that their content is less misunderstood, and the communication is more thought through since they interact with AI. Engaging professionals with different backgrounds such as a manager

and a developer used to be difficult due to specific language and reasoning. Through AI, their communication gains clarity and neutral explanations: "It helps a lot in bridging these miscommunications" (M4). Moreover, the partnership becomes visible through how managers frequently give generative AI nicknames, such as "live coach" (M2) or their "own little tutor" (M3). Additionally, in some cases, managers bring AI into the physical world during meetings by discussing in groups with AI either on a shared Microsoft Teams screen or on a physical screen in a meeting room. One manager describes their group work as such:

> We were actually programming yesterday, me and my team, and I said like this: 'What should I do now? What should I ask Copilot?' And then three other developers were sitting there, and I said: 'What am I even going to do with you?' The Copilot had the right answer right away – M13

The partnership takes over a role where many describe that they can no longer imagine a life without AI. It is incorporated into the managers' everyday life and interactions with AI turn into an automatism. One interviewee summarizes the partnership as: "I almost see AI as a colleague" (M12). At the same time, managers identify differences between a human being and the human resemblance of AI. On the one hand, AI does not fulfill all human characteristics. Unlike human colleagues, generative AI does not understand the detailed company's internal context. Some report that the quality is not always sufficient as generative AI does not understand implied context like the managers' age or the company the manager works at, that contributes to answering a question. One interviewee describes AI's missing context:

> It doesn't see how I'm sitting here; it doesn't know me; it doesn't see what stuff is on the wall behind me. So it only has the information it gets from me – M19

Others underline the company's internal language that AI does not understand. Counterquestions would support AI's understanding of the context, however, contrary to humans, AI does not ask questions by itself. The respondents wish for an independent engagement of AI in identifying that prompts might be misleading and need further refinements. Moreover, if managers provide AI with context, some report that it also forgets its persona and context over time. Unlike human coworkers, AI shows a limited capacity to remember thereby basing interactions with the managers only on the most recent prompts despite having a long-running conversation. On the other hand, managers seek group cohesion that cannot be replaced by generative AI. While some report that the physical component such as personal contact and body language is missing, others underline the lack of "social interactions" (M4) and "real communications" (M15) which are still needed. Human interactions show to create unique feelings of comrades and social belonging. One interviewee highlights different excitements between interacting with AI and colleagues:

> If you talk to a colleague, it becomes more of a conversation and not as concise and boring. (…) If you only had an AI assistant compared to having colleagues to talk to, it would be boring – M11

Finally, human experience remains highly valued, and trust in colleagues is shown to be higher than in AI. After all, final presentations of the results, despite being conjointly created with AI, remain a task of the manager.

Discussion

In exploring the interactions of generative AI and managers one can identify an evolving process of forming a relationship. The key dimensions that have been developed in the data analysis: support, hesitation, validation and partnership, prove to be interactions that form relation stages between AI and the manager (Barad, 2003). Thereby, the relationship is created in four subsequential stages moving from managers perceiving AI's role as a junior assistant to AI becoming a colleague for the manager (see Table 3). These roles result from direct quotations from the interviewees. Orlikowski and Scott (2008) refer to the relationship as a creation of practices: "Relations are enacted in recurrent activities" (p. 462). Consequently, different practices also lead to different stages within this relationship process.

Perspective	Interaction	AI Role	Affordances	Constraints
Tool	Support	"Junior Assistant"	AI can take over routine-based and time-consuming tasks that require low responsibility and low knowledge on the task	Trust on AI is highly limited and tasks that include decision-making are excluded from the relationship
	Hesitation	"External Freelancer"	The relationship is considered to be worthy of adapting and altering routines to gain better results from AI	Trust and responsibility are sensitive topics in terms of data security and slow down the adaptation
Collaboration	Validation	"Knowledge-able Person"	AI shows to have high knowledge and can help the manager in overcoming barriers of insecurity, and context understanding. The responsibility is extended to providing drafts and proposals	Trust for AI is still limited through hallucination and misunderstanding. Managers remain responsible by including strong reflections on the sources and wording of AI
	Partnership	"Buddy" and "Colleague"	The relationship is comparable to a human one, including high trust and low reflection. It extends to managers feeling more comfortable with AI than humans over certain areas	Trust in human colleagues is higher valued because AI cannot provide solidarity

Table 3. Evolving relationship between managers and generative AI

The evolving process of forming a relationship is presented in Table 3 above. Based on the analysis, the managers in the tech field do not always follow the sequential process. Individual

forms of the relationship may be omitted as the interactions are not embodied in the technology but are an enactment of the human and material (Leonardi, 2013b). However, for the majority of the interviewees, there is a linear sequence in which the managers sometimes remained in one relational stage, influenced by the previous steps, and are not formalized up to the final relationship of the colleague. This aligns with Leonardi's (2011) understanding of imbrication, meaning that past interactions accumulate over time causing human and material agencies to change in the process. Consequently, the discussion is based on the process of forming a relationship constituted by the interactions that influence managers' perception of the AI role, which ultimately result in affordances and constraints affecting every stage of the relationship.

Tool perspective

When entering the relationship, the managers reveal to view their AI interactions from a tool perspective. Through a phase of trial-and-error managers identify AI as a tool in their managerial practices. Thereby the perception of a tool is not inherent in the attributes of AI but comes out of sociomaterial enactments (Orlikowski, 2000). The interactions are shaped by the manager's realization of benefits in their work life and limitations in AI's capabilities driven by an explorative interpretation of generative AI.

The first stage that the manager and AI engage in, is that of a junior assistant. In this stage of the relationship, the manager sets the goal of reducing the daily workload by interacting with AI. The managerial aspiration to accelerate their pace of work can also be found in previous managerial AI studies (Lifshitz-Assaf et al., 2021) and transfers into supportive interactions with generative AI, which the managers equate with a junior assistant. Managers respond to AI conducting managerial tasks by implementing new creative practices and by feeling relief from unnecessary duties. The material and human agency are not possessed by either the manager or the AI but come out of the interactions (Leonardi, 2011) causing each manager to conceive different support functions.

The human and material interactions result in both affordance and constraint based on the manager's perception of whether AI is able to achieve the intended goal (Leonardi, 2011). The manager has set the objective of reducing the daily workload through AI interaction leading to the affordance that AI assists in routine tasks that require low knowledge and responsibility and allows the manager to be more time efficient. Thereby AI can take over mundane tasks and allow the manager to focus on creative practices (Jarrahi, 2018). Nevertheless, it is also possible to recognize constraints on the relation in the limitation of AI to practices of low responsibility and the exclusion of strategic practices such as decision-making. Managers keep taking on complex tasks and cannot feel a workload reduction in all managerial practices (Korzynski et al., 2023). This is based on the manager's limited trust in AI as this relationship shows to be still at an early and explorative stage. Previous research on technology constraints has highlighted accuracy and transparency as barriers to human-AI interactions (Cranefield et al., 2022) that have also been mentioned by the interviewees and may contribute to their low trust in Al.

As the managers aim for support in work practices, they allow for the technology to perform parts of the managerial practices and consequently respond with an efficient change in time allocation for tasks. This resonates with Leonardi's (2011) view of a catalyst that is the

actor that initiates the change in routines and practices. Thereby, in this stage, the data suggests that managers initiate the formation by identifying the benefits of support in AI.

The second stage is that of AI's role as an external freelancer, which corresponds to the dimension of hesitation from the data analysis. To engage in the relationship, generative AI needs to be incorporated into the daily practices of the manager and gain access to data. Consequently, managers change their work habits by learning how to prompt or change their standard search engine from Google to ChatGPT resulting in new routines (Leonardi, 2011). In the prompts, AI gains data availability of internal, external, or private data that it uses to refine its results (Chen et al., 2023). The potential data leakage has been acknowledged as a risk of interacting with AI by the managers. Most of the interviewees reported how AI collects information through the written prompts. Consequently, managers do not proactively provide data availability but the AI acts upon the manager (Styre, 2017) by making the manager reveal to some degree sensible information. Thereon managers feel a loss of control resonating with an opaque tool that cannot be acted upon (Kellogg et al., 2020). In this relation, managers identify AI as an external freelancer who does not show to be in close relation to the manager but rather is seen as an external actor. This opposes obstacles to the manager to engage in this relation. Since the work practices regard data access and changed work habits, the interaction is characterized by hesitation and AI is still not regarded in a liaising manner. Thereby managers do not set a direct goal for this relation but try to accommodate the obstacles.

The observable affordance is based on the manager's evaluation of whether it is worth adapting their practices to interact with AI. The manager must invest time and effort to learn. If human agency can be observed through practices of changed work habits, the technology affords the manager to consider the relation worthy enough to accommodate (Leonardi, 2011). It is imperative that managers need to be aware of the needs for a relation and willingly adapt to it (Zhang et al., 2021). The constraint is however that both trust and responsibility are subjects that slow down the adaptation and the learning process for the managers (Cranefield et al., 2022). These human and material agencies need to be enacted, meaning managers and AI need to engage in the practices, (Jones, 2014) otherwise the relationship cannot form, and managers cannot benefit from AI (Cranefield et al., 2022). This shows in some managers deciding to no longer engage with AI and exit the relationship. The hesitation in AI comes out of the low trust when providing AI with data and not wanting to risk potential data leakage. The fear of data leakage might be connected to the opaque characteristics of algorithmic learning causing low trust if managers cannot understand the AI system and who can access the data (Chowdhury et al., 2022). The affordances and constraints are evaluated against one another if it is worth the time and risk to learn and adapt.

While Leonardi (2011) based the catalyst on human perceptions, one can identify that machines can also initiate the formation of a relation through changes in practice. In the second stage, AI can be seen as the catalyst that initiates the new routines and practices becathe uncertainty that AI inhabits leads to hesitations that interact through adaptations of the manager and accommodations of AI. The manager does not intentionally set a goal for this interaction but rather adapts to the AI to continue the relationship process (Zhang et al., 2021).

Collaboration perspective

Moving from a tool perspective to a collaboration perspective, managers acknowledge that a relationship with AI consists of adjusting practices to overcome risks of data privacy and trustworthiness. This change in practices leads to a reconfiguration of the technological attributes (Orlikowski & Scott, 2008) resonating with a human-like collaboration. The collaboration is shown to be an intentional interaction between managers and AI in which managers knowingly adjust their practices while responding to the identified characteristics of AI (Orlikowski, 2000). This willingness to respond to technologies in practice is based on a recognition of the affordances and constraints of the manager (Leonardi, 2011).

The third stage of the relationship between managers and AI is that of a knowledgeable person, in which the interaction is more complex. The relation is formed by a two-sided validation helping the manager to overcome the hesitation of the second relation leading to an entanglement of the human and material so that they are perceived as inseparable (Orlikowski & Scott, 2008). Managers are not only validated by AI, but they also validate AI. On the one hand, the manager sets the goal of being validated through AI. Thereby AI provides reassurance by either confirming or contradicting managerial opinions on topics. On the other hand, managers reflect on the provided results from AI and create the new practice of fact-checking against AI. In order to do so managers need to have confidence in their validation capabilities to avoid false interpretations from AI (Lebovitz et al., 2021). At the same time, managers do not want to publish texts to their colleagues that are fully generated by AI. Due to the manager's perception that AI results are distinguishable from the manager's own work and do not fulfil the managerial expectations, managers personalize the provided texts from AI. Because AI provides the basis for managerial work through their interactions, AI participates in managerial practices (Korzynski et al., 2023). This entwinement of managers and AI into managerial practices leads to AI questioning who becomes responsible for their co-creative work. Managerial practices are no longer solely done by human workers but are co-created by managers and AI (Wilson & Daughtery, 2018). Consequently, the entanglement of sociomaterial practices becomes evident, as a clear distinction on whether AI or managers have done the duties becomes challenging (Scott & Orlikowski, 2014).

Within this stage, managers realize the knowledge of AI and its ability to both help with uncertain questions for the managers while also understanding context better. Thereby they identify the benefit of AI as a validation and see an augmentation of the managerial work through generative AI (Dwivedi et al., 2023; Raisch & Krakowski, 2021). Consequently, affordance is extended by AI's ability to do more complex practices, such as the creation of proposals and increase AI's responsibility (Leonardi, 2011). Managers feel comfortable with letting AI generate early base material such as proposals and drafts and can help the managers overcome insecurities when they feel uncertain over a topic. However, managers still notice the constraints of AI hallucinating and misunderstanding context and thereby keep a limited trust in AI. Although managers validate AI's results the risk of overlooking vague or false statements remains. Unlike the second relation, managers show the goal of actively maintaining the relationship and changing their practices to benefit from AI's validation (Leonardi, 2007). By fact-checking and personalization, the texts generated through managers and AI become less noticeable and seem to be invisible to their human colleagues. This might be a response to

the accountability gap that is caused because the co-creation of work makes it difficult to attribute a specific outcome to one actor (Mittelstadt et al., 2016).

Within the interaction of validation, one can observe that the practices are initiated by both the manager and the AI. Since the manager aims for reassurance and AI shows constraints in accountability initiating practices of validation for both actors. Therefore, the data suggests that both managers and AI become the catalysts for changing the practices of the relationship (Leonardi, 2011). Due to the entanglement of the validation practices the necessity for one initiation to precede the other is negated (Scott & Orlikowski, 2014).

The fourth and last observable stage is that of a buddy and a colleague. In this stage of the relationship, human and AI interactions become visibly entangled in a partnership. On the one hand, the manager's goal is to have a communication partner that is twenty-four seven available, an expectation set by generative AI's human-like communication. Because managers can communicate with AI as if it were human, managers change their routines of approaching AI instead of their co-workers and thereby replace their colleagues to some extent, indicating that AI might have an influence on employment in the future (Dixon et al., 2021). The entanglement of communication practices is revealed in the two-sided human-like discussions between the manager and AI. Orlikowski (2010) describes the sociomaterial entanglement in practice as the "dynamic sociomaterial configuration performed in practice" and further adds that "the social and material are inseparable" (p. 136). On the other hand, generative AI cannot provide solidarity which leads to managers seeking group cohesion. Consequently, AI is not perceived as a full human being and lacks contextuality, initiative and human belonging.

The perceived affordance by the manager concerns how both trust and responsibility increase in this relationship, as the manager at times feels more comfortable interacting with AI than with colleagues. Thereby, AI affords the manager to be less dependent on the co-workers as managers trust AI with sensible topics such as cases of death and gain comfort because they have an interaction partner during weekends and late working hours. Nevertheless, the perceived constraint is that the manager never trusts AI to such an extent as they do with a colleague because AI does not provide human solidarity and contextuality. AI cannot provide the joy managers have in human interactions and managers need to explain everything AI needs to know. This is because AI cannot act upon itself. The material agency is based on sociomaterial interactions (Leonardi, 2011) and is not something the material inherently possesses (Barad, 2003).

This stage of the relationship marks the last observable process in forming a relationship between managers and AI in which AI is most closely knit to the manager. Whilst in the validation the managers are aiming to maintain the relationship, now moving on to the partnership they acknowledge that it is maintained and the relationship becomes a trustworthy partnership. According to Jarrahi (2018), a synergic partnership is articulated in humans and machines where the "strengths of one compensate the limitations of the other" (p. 579). Managers have identified that AI becomes a discussant partner due to its strength in availability when their colleagues are unavailable. They set the intention to form a human partnership and form human-like practices of AI while AI initiates a reflection on group cohesion (Leonardi, 2011). When referring to AI as a buddy or colleague managers make the partnership visible and demonstrate that they are not concerned about their interactions with AI becoming observable to their colleagues. Rather they are proud that through the partnership they no longer

need to disturb their colleagues. Acknowledging the partnership can be transferred to the sociomaterial context as acknowledging the sociomaterial entanglement (Scott & Orlikowski, 2014). Managers indicate that they cannot envisage their managerial practices without AI. Nevertheless, the manager does not perceive AI as an equal to a human being, and managers compensate for it through strong valuations of group cohesion. Perceiving AI with its human and non-human characteristics is a recursive process that is different for each manager and is constantly recreated (Orlikowski, 2000).

Evolving process of forming a collaboration

The evolving relationship between generative AI and managers describes the process of forming a collaboration. Previous research has called for a move from a tool perspective to a collaboration perspective (Anthony et al., 2023). However, in this research, one can identify that these perspectives are not contradictory but part of a processual transformation. By describing generative AI as a junior assistant and external freelancer managers engage in a one-sided relation. Either a managerial or material intention is shaping the relation (Leonardi, 2011). This resonates with a tool perspective where managers simply use AI to gain more time and AI needs to be integrated into the daily workflow (Faraj et al., 2018; Kellogg et al., 2020; Rosenblat, 2019). The first two relation stages are perceived as beneficial but also obstacle-driven relations by the managers. This can be seen by affordances in simple tasks and constraints in trust and responsibility.

Moving from hesitation to validation interactions one can understand that a new narrative is driving the relationship. Narratives are interpretations of life (Czarniawska, 2004) and show that managers perceive the relationship differently along the formation of a colleague. Within the process, managers start to discuss responsibility over tasks and AI gains trust not only in its performance but also in guiding the manager through their daily work. This narrative shift can be theoretically found in the entanglement of the social and material (Orlikowski & Scott, 2008). In both interactions of validation and partnership, the entanglement between human and material agency, initiated by the manager and AI, is identified. This entanglement of the agency is forming a collaboration. Managers and generative AI are perceived in these relations as agents conjointly engaging in the interaction process (Murray et al., 2020). Collective agency of managers and generative AI is a key criterion in forming a collaboration and moving from using AI to collaborating with AI (Lebovitz et al., 2022; Michel, 2020). In AI's role of a knowledgeable person, it can be acknowledged that the entanglement of agency becomes a two-sided intention of validation. The intentionality of the manager to change routines and maintain the relationship (Leonardi, 2011) leads to a switch from a tool to a collaboration perspective. However, this relation is formed by a personalization practice that aims to hide the interaction practices. Thereby this relation stage is identified as a form of invisible collaboration. The fourth stage of the relationship, described as a colleague, is shaped by managers replacing interactions with partners through interactions with AI. Trust is created between managers and AI to a degree of trusting AI with sensitive topics and valuing its opinion and all-time availability. In the final stage of the relationship, managers acknowledge the role generative AI has taken on in their lives and thereby form a visible collaboration. Thereby we can illustrate not only a narrative shift around AI in academia (Anthony et al., 2023), but also

demonstrate that managers undergo a change in narratives through words like buddy and colleague and make the collaboration visible for themselves.

Partnership as the final stage of the collaboration

The evolving relationship between managers and AI ends in the stage of a partner based on the collected data. Nevertheless, generative AI is a fast-changing technology, constantly updating its underlying algorithm (Tse et al., 2024) and thereby confirming the constant state of fluctuations of technologies (Baldwin & Clark, 2000). Fast-paced developments of AI could enable the relationship to reach new stages as time progresses. At the moment of the research and on this micro perspective between managers and AI one can identify stable characteristics that form the relation (Bailey et al., 2022). Generative AI is shown to be missing significant human characteristics especially based on tacit knowledge, meaning the embodied knowledge through experience. Thereby, tacit knowledge remains an advantage managers have over algorithmic learning (Shestakofsky, 2017). Although a visible collaboration with AI is identifiable, human colleagues are still considered to be more trustworthy and valued. The entangled agencies are not evolving further as interpretations are stabilized for the moment (Orlikowski, 1992) and thereby create an interagency relationship (Leonardi, 2011). Consequently, trust and solidarity are currently limiting a possible fifth stage of the relationship. Yet, technologies are not stabilized for long (Bailey et al., 2022). Through adaptations in the relational interactions either by the engagement of developers in altering the capabilities of AI or by changes in managerial practices or objectives, the relationship might evolve further (Orlikowski, 1992).

Although management and organization journals have discussed the potential of decision-making with algorithmic learning, especially in the case of generative AI (Anthony et al., 2023; von Krogh, 2018), managers have not recalled interactions in which AI had agency over decision-making. Despite that the interviewees work in different organizations and represent a broader field of managers, no one explains a decision based on AI but rather highlights how they would not trust AI with decision-making. Although seeking support in AI with inspiration is categorized under the decision-making process, it is only the initial step of a decision (Doya, 2008). The relationship of validation contradicts existing studies on algorithmic learning based decisions in which managers solely rely on the AI output instead of reflecting on the suggestions (Lindebaum et al., 2020; Murray et al., 2020). This indicates that generative AI is currently not an example of delegated decision-making authority (von Krogh, 2018). This research suggests that the reason for the limited engagement in decision-making is the reduced trust from managers in generative AI within the relationship causing constraints in the relation. Not only is trust an important criterion for forming a collaboration but it is also crucial for joint decision-making (Henderson & Smith-King, 2015). While trust between managers and AI increases within the evolving relationship and finally is strong enough for a collaboration it never reaches a sufficient level for decision-making.

As managers and AI are forming a relationship, there is not always a full development of all four stages since some managers for example only perceive the AI relation as a junior assistant and it never evolves into a buddy or a colleague. This could be because individual managers do not feel that AI is helping them to achieve their objectives. Affordances and

constraints are based on perceptions of objectives that can affect choices being made for new work practices and routines (Leonardi, 2011). The manager's functional need for AI is an individual perception that can vary (Bailey et al., 2022). Through this thesis, we can say that the changes in AI relations can come out of reinterpretations of affordances and constraints (Leonardi, 2011) but cannot draw any conclusions about how the emergent process occurs in specific cases (Orlikowski, 2000). This research implies that the evolving trust is driven by an interpretation of fears and risks rather than by harmful experiences. In fact, no interviewee recalls a situation with actual negative consequences. Rather trust might be increased through positive interactions such as AI providing one with insightful information resulting in increased responsibility for the relation. Future research is required to conclude how trust and responsibility emerge in specific cases.

Limitations and Directions for Future Research

The limitations of this study can be found in the research sample. The source of the analysis was based on interviews with managers in the tech field looking at one side of the human-AI relationship. Although the aim was to identify AI practices equally and to let AI speak through managers' reflections, the method showed limitations when it came to foregrounding the technology. In the interviews, managers emphasized their personal practices, and it was up to us researchers to identify AI practices. This might have led to incompleteness. Research suggestions to make AI speak for itself have been identified in the past by analyzing the collected data from AI (Cecez-Kecmanovic et al., 2014). However, it was unfeasible for us to gain access from Microsoft and OpenAI. Moreover, out of our open interview requests, only four female managers in the tech field responded positively. Male and female engagement within work relations differs (Merluzzi, 2017) leading to this relationship study representing rather the male relationship with generative AI. A more female-focused study would be interesting in the future as the entangled relationship might differ.

This research examines the relational spectrum of managers in the tech field and text-based generative AI. Building on this relationship study it will be interesting to ascertain to what extent the process of forming a collaboration is applicable with image-based generative AI or other human actors. This study focuses on the human-AI relation from a micro perspective with the potential of further extension to the macro level of organizations (Leonardi, 2013b). Thereby, it enables the understanding of whether a partnership is also formed within a larger team or even an entire organization, and if the process also shows a transition from a tool perspective into a collaboration perspective. According to Leonardi (2013b) "micro-level action [that] aggregate[d] into macro-level organizational structure" (p. 64), suggesting that the formed relationship between managers and AI might transfer into the organizational context. Some interviewees highlight that they incorporate generative AI into their external team meetings providing an interesting ground for further studies on organizational relations. This can be done through a zooming-in zooming-out perspective allowing for a dynamic emerging relation study (Nicolini, 2009) that allows for a reinterpretation of the results into one organizational context across one team over a longer time period. The data suggests that generative AI could extend to organizational relations and could become an additional colleague in a team of multiple people. Nevertheless, emerging

research on leadership suggests that employees react differently to human managers than to AI researchers (de Cremer, 2020), making it valuable to review how human-AI collaboration, like those in this research, is perceived by both employees and colleague managers.

Conclusion

Technologies like ChatGPT and Copilot engage with managers in a relational process that moves beyond a tool and forms into a collaboration. Allowing the possibility of a human-AI partnership indicates a shift in organizational dynamics where colleagues are no longer exclusively human but can also include AI-driven entities. For these collaborations to be effective, organizations should cultivate trust and responsibility with AI systems. This involves paying careful attention to the user interface design, result quality, ethics, and data security. Companies should strive to accommodate these factors to support seamless integration. When preparing to interact with AI, it is crucial for the manager to reflect on the individual goals of the interaction to identify the most suitable type of relationship. Expectation management becomes important as it influences perceptions of technology's usefulness and satisfaction (Buschmeyer et al., 2022). A collaborative partnership requires more practices and effort than assigning tasks to a digital assistant in the form of a tool, so being intentional about how to integrate AI can lead to more productive interactions. Generative AI is not one-sided but involves both material and human interaction that have to be managed. Managers need to be aware of the emerging trust within the relationship both in terms of developing and mediating trust to avoid a blind-sided interaction where AI's capabilities could be either valued too high in the collaboration or too low in the tool perspective. Unlike other technologies with predictable usage patterns, generative AI demands nuanced management due to the intertwined influence of algorithms and managerial practices.

The purpose of this research was to understand the formation of a relationship between managers and generative AI. Following the literature on collaboration we wanted to gain insights into the relationship that is shaped by the interactions and practices. It showed that managers and AI initiate a process of four stages to form a relationship that can be seen in changing affordances and constraints and evolves into a partnership. Based on a sociomaterial framework we investigated the interactions within the relationship. Material and human practices, that create an interaction, were present at each stage of the relationship but were seen as sequential in the first two and as entangled in the last two. Concluding, generative AI can become a colleague in a relationship with the manager shaped by an interaction of agencies. Thereby, we have contributed to management studies in three ways.

First, generative AI proves to be a suitable example of the interwoven human and material interactions (Leonardi, 2011). Whilst relational sociomateriality in algorithmic learning has been more of a theoretical concept in the past (Bailey et al., 2022; van Rijmenam & Logue, 2021) we can identify its relevance in empirical data. Previous empirical research on sociomateriality has been focused on affordances and constraints (Cranefield et al., 2022). Combining this concept with Orlikowski's (2000) practice lens allows us to acknowledge that affordances and constraints differ not only across context but also in the relationship process of an individual manager. This proves that attributes of a tool or collaboration are not inherent in the technology but emerging in the interactions (Orlikowski & Scott, 2008). Moreover, the

initiations of practices which Leonardi defines as a catalyst (2011), are not only seen as being human but the study shows that the catalyst for practices can also be in technology.

Second, this paper acknowledges that managers and AI can engage in a collaboration. Contrary to previous research on collaboration (Anthony et al., 2023), this study demonstrates that a change in perspective from tool to collaboration is not simply a theoretical construct but rather the result of a process of interactions. The manager's perspective on AI is influenced by their intention to actively engage in the relationship. Therefore, research on collaboration needs to account for the transition from a tool to a collaborative entity and become more flexible.

Third, managerial practices can be performed through joint interactions between managers and AI in which AI becomes a colleague of the manager. However, this role of AI requires a process that the managers actively need to engage in and overcome opacity. This stage does not simply happen to the manager, but an intentional entanglement of human and material agency leads to this position. Nevertheless, AI continues to show differences between a human colleague and cannot fully replace the manager's colleagues in the "real world".

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