Hello, Mate! Insights from the Field on Leveraging Machine Teammates in Organizations

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Completed Research Paper

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Abstract

Fueled by recent developments in Artificial Intelligence (AI), systems move from passive advisory tools to active co-creating teammates. For organizations to be able to fully leverage the potential associated with these powerful human-machine teams, their positive effects need to be fostered, while negative effects of the implementation need to be mitigated. We use the socio-technical-systems perspective to holistically explore factors that helped organizations in integrating AI-enabled machine teammates for content creation purposes. Based on 32 expert interviews, we delineate six facilitators, seven inhibitors, as well as six task-related and structure-related influential factors. We further reveal inadvertent paradoxical effects that can emerge upon fostering facilitators, which can, in turn, obstruct the positive effects associated with the facilitators. With these insights, we contribute an explorative post-adoption perspective that can help organizations leverage machine teammates. We also aid the theorizing on newly emerging phenomena in the era of increasingly collaborative and agentic systems.

Keywords: Artificial intelligence, machines as teammates, organization, socio-technical-systems

Introduction

One of the most influential technological advances of our time, Artificial Intelligence (AI), substantially challenges the assumptions that prevailed in Information Systems (IS) research and opens up new opportunities for business conduct. Chatbots can handle customer service functions, while clinical decision support systems (DSS) improve doctors' diagnostics of brain scans. Yet, instead of taking support functions or passively advising humans, increasingly powerful AI-enabled systems can now also engage as co-creators of firms' core products. For example, so-called 'robo-journalists' work alongside human journalists to create a compelling content portfolio. Hereby, they do not only support journalists in content creation but also contribute own articles. This new generation of systems allows organizations to move away from the currently dominating advisory systems, which passively support their users in decisions (Enholm et al. 2021). Instead, organizations can now leverage performative systems, which take an active role and assume responsibility in independently executing actions in bilateral interactions (Schuetz and Venkatesh 2020).

In contrast to the dystopic prediction that organizations will replace humans with AI, the notion of forming synergistic teams of humans and AI peers has gained momentum (Seeber et al. 2020). Teaming is a long-standing, powerful tool to improve organizational outcomes (Kozlowski and Ilgen 2006). Machines moving from the status of a tool to the status of a teammate, i.e. humans and machines collaboratively engaging in co-creation in an interdependent manner (Rix 2022), induces similarly positive outcomes as human teaming (Walliser et al. 2019). Hereby, machine teammates combine the automation of tasks, i.e. the machine taking over a task, and augmentation of humans, i.e. the machine empowering humans in a specific task. The teaming setting combined with this balance between automation and augmentation maximizes the potential positive impacts of AI-enabled system introduction on organizational performance (Raisch and Krakowski 2021; Seeber et al. 2020). Accordingly, the formation of human-machine teams is a valuable lever for organizations (Seeber et al. 2020). However, these increasingly collaborative and agentic systems make the classical view of IS in organizations "increasingly obsolete" (Baskerville et al. 2020, p. 509). The traditionally prevailing concept of 'system use' in the IS discipline is challenged (Baird and Maruping 2021; Schuetz and Venkatesh 2020). Thus, extant insights on integrating (advisory) IS in organizations are not fully applicable to human-machine teams. Accordingly, IS research needs to develop an "understanding of how humans and AI technologies interact in new ways" (Benbya et al. 2021, p. 281-282) to allow organizations to realize the potential associated with the introduction of this next generation of systems.

Based on these contentions, a research stream on machines as teammates emerged (Seeber et al. 2020). This stream includes studies on designing machine teammates (Wiethof et al. 2021), their potential roles (Siemon et al. 2020), or the effect of specific machine teammate configurations (Bogg et al. 2021). Even though the most considerable potential for machine teammates lies in the organizational context, they have not yet been studied in the organizational field (Seeber et al. 2020). Inquiries into the application of machine teammates in organizations are especially important given the hypothesized fundamental change to organizational conduct, design, and coordination upon the introduction of these forms of performative AI-enabled systems (Enholm et al. 2021). Further, despite a high magnitude of unforeseen consequences associated with the introduction of these systems (Raisch and Krakowski 2021; Riemer and Peter 2020), research with a post-adoption perspective on performative systems in organizations is scarce (Jöhnk et al. 2021). Hence, for organizations to be able to leverage the vast potential of machine teammates, research needs to inquire into "how to better utilize positive effects while mitigating potential negative effects" (Diederich et al. 2022, p. 114). Consequently, understanding how organizations can effectively implement machine teammates based on an explorative post-adoption inquiry in the field can fill a significant gap of high theoretical and practical relevance. Accordingly, we fill this gap by asking:

RQ: *What factors facilitate or inhibit the effective integration of machine teammates into organizations?*

Inquiries into organizational integration of AI-enabled systems should consider not only machine-related but also affective, human-related factors (Baskerville et al. 2020), especially regarding machine teammates (Seeber et al. 2020). To ensure a holistic view of the entire technosocial system, the Socio-Technical-Systems (STS) perspective, which recognizes the interdependence of the social and technical components in organizational deployment of technology, can be leveraged (Makarius et al. 2020; Niehaus and Wiesche 2021). AI-enabled systems for content creation purposes are early examples of performative systems that are already quite widely diffused into organizations. Thus, they present a valuable underlying use case for inquiring into machines as teammates in the field (Memmert and Bittner 2022). We have interviewed 32 experts that were directly involved in the organizational deployment of machine teammates for content creation. Based hereon, we identify facilitators and inhibitors of as well as influencing factors on organizational integration of machine teammates. Further, we reveal paradoxical effects of the facilitators, as, for example, fostering a higher work-life quality or configuring the machine teammate for serendipity can inadvertently trigger negative consequences. With these insights, we contribute guidance derived from a post-adoption perspective for organizations that plan to leverage machine teammates that automate and augment simultaneously (Raisch and Krakowski 2021). We further contribute to the call of research for empirical insights from the field for the research notion of machines as teammates (Seeber et al. 2020). Finally, this study can also aid the 'new generation of use' theorizing by providing insights into novel phenomena emerging with the new generation of increasingly agentic systems (Baird and Maruping 2021).

Related Research and Theoretical Lens

AI-enabled Systems in Organizations

AI refers to the capabilities of IT systems that require some form of human intelligence (Rzepka and Berger 2018). Systems with AI capabilities can be subsumed as AI-enabled systems, which encompass AI-enhanced (e.g. intelligent DSS) as well as AI-based systems (e.g. chatbots) (Rzepka and Berger 2018). Traditionally, organizations implemented AI-enabled systems to either automate routine processes (e.g. robotic process automation) or augment humans through advice (e.g. DSS) (Benbya et al. 2021; Raisch and

Krakowski 2021). While automation embraces the substitution of humans, augmentation helps humans overcome cognitive boundaries (Enholm et al. 2021; Raisch and Krakowski 2021). However, recent advances in machine learning (ML)-based technologies allow IT artifacts to learn, adjust behaviors, and autonomously execute actions, moving from rule-based to intelligent conduct (Rzepka and Berger 2018). Combined with enhanced computing power and exponential data increases, a new class of increasingly agentic and collaborative performative systems emerged (Baird and Maruping 2021). This new generation of systems is able to honor the interdependence of automation and augmentation by balancing both concepts. This integration maximizes organizational outcomes (Raisch and Krakowski 2021). Thus, the focus shifts from advisory systems to performative systems, which can independently execute actions.

Despite the vast potential of these systems, the research on AI-enabled systems in organizations, and especially performative systems, is still in its infancy (Jöhnk et al. 2021). This may be grounded in the pilot and experimental character of many AI projects (Benbya et al. 2021). Research on AI-enabled systems in organizations can be divided into two phases. First, research on the pre-adoption phase of AI investigates factors to consider before the implementation of AI into an organization, such as AI readiness factors (Demlehner and Laumer 2020; Jöhnk et al. 2021), suitable use cases and roles for AI-enabled systems (Engel et al. 2021; Siemon et al. 2020), factors influencing the adoption of AI (Radhakrishnan and Gupta 2021) or creating business value with AI (Enholm et al. 2021). Second, research on the AI post-adoption phase embraces factors to consider during the process of integrating AI, such as ethical guidelines (Seppälä et al. 2021), as well as research aimed at identifying and effectively managing the effects of AI-enabled systems on organizations. The latter includes inquiries into the effects on employees' identity (Mirbabaie et al. 2022; Strich et al. 2021) or organizational performance and creativity (Mikalef and Gupta 2021).

Especially research presenting empirical insights post to adopting an AI-enabled system is scarce, hence there is a lack of understanding on how AI-enabled systems are used in organizations (Enholm et al. 2021). However, holistically understanding employees' interaction with and implications of the AI-enabled system is integral for employees' acceptance of these systems and thus organizations' ability to leverage them (Diederich et al. 2022; Makarius et al. 2020). Further, many studies solely focus on general AI and do not distinguish between advisory and performative systems (Hamm and Klesel 2021; Radhakrishnan and Gupta 2021). Also, a dominant focus on advisory systems, i.e. systems taking a supportive instead of a peer-like role, can be observed from extant literature (Jussupow et al. 2020). As these two distinct system types may hold significantly different implications, dedicated inquiries into the effects of performative systems are important (Diederich et al. 2022; Jöhnk et al. 2021). Combining the lack of post-adoption research with the lack of performative system research, inquiring into post-adoption phenomena of implementing performative AI-enabled systems presents a worthwhile line of inquiry. Hereby, outcomes for organizations are maximized if these performative systems are integrated as teammates (Walliser et al. 2019). Thus, this form of integrating systems, herein interchangeably referred to as machines, presents a worthwhile avenue for extending the knowledge on integrating AI-enabled systems into organizations (Seeber et al. 2020).

Machines as Teammates

As outlined earlier, the accelerating capabilities of AI-enabled systems allow for the emergence of systems as (prescriptive) agents and an ontological reversal, manifesting a turning point for IS research regarding the interaction with IT artifacts (Baird and Maruping 2021; Baskerville et al. 2020). As a result, "AI changes not only its own standing within the IS discipline, but also the dimension of the interaction between itself and its human counterparts" (Niehaus and Wiesche 2021, p. 2). Instead of the traditional unidirectional system use, in which a human provides a request to a system, which then, in turn, delivers a result, the newly emerging capabilities and agency of AI-enabled systems push towards the emergence of bilateral interactions (Schuetz and Venkatesh 2020). Hereby, both parties push and pull information and engage in the exchange of work products (Panganiban et al. 2020). The research notion on machines as teammates takes these dimensional changes into account and presents an approach to the 'new generation of use' theorizing required in the IS research discipline (Baird and Maruping 2021; Rix 2022). It builds on humans' tendency to consider systems as social actors and transfer human-to-human behavioral patterns and heuristics into the human-machine interaction context (Nass and Moon 2000). Accordingly, the insights from human teaming, a highly effective form of organizing work in organizations, can be used to theorize on the newly emerging forms of human-machine interaction (Rix 2022; Seeber et al. 2020).

The novel conceptualization of human-machine interaction in the form of human-machine teaming (HMT) can be described as a sub-form of human-machine collaboration. Collaboration builds the basis for teamwork and thus serves as a prerequisite for the emergence of HMT (Memmert and Bittner 2022; Rix 2022). Collaboration is "an evolving process whereby two or more social entities actively and reciprocally engage in joint activities aimed at achieving at least one shared goal" (Bedwell et al. 2012, p. 130). Team formation drivers change humans' perception from being part of a collaborative group to being part of a team, transforming taskwork, as in human-machine collaboration, into the more effective form of teamwork, as in HMT (Kozlowski and Ilgen 2006; Rix 2022). Yet, there is no uniform set of minimum viable requirements for teamwork to manifest with a machine. In line with extant research, we consider two requirements derived from human teaming and HMT literature for HMT to emerge: the manifestation of interdependency and co-creation (Kozlowski and Ilgen 2006; Memmert and Bittner 2022; Rix 2022). Interdependency, for example, emerges when humans become dependent on the machine teammate for being able to fulfill the team's workload and achieve their performance goals (Rix 2022). Co-creating the final outcome implies that machine teammates take an active part in the interaction and equally contribute to the final outcome, thus passive recommendations do not suffice for teamwork to manifest (Memmert and Bittner 2022). In summary, we define the prerequisites for the emergence of HMT by the manifestation of a collaboration situation, i.e. a process involving at least two entities engaging in reciprocal interaction towards a shared goal, in which human and machine team members engage in interdependent co-creation.

Three major lines of research emerge in HMT research: team formation, teaming processes, and teaming outcomes (see Table 1). The research on team formation mainly focuses on design science for machine teammates, while one study also takes an interview approach (Zhang et al. 2021). Research on teaming processes investigates emerging behavioral patterns in human-machine teams. Finally, the research on teaming outcomes reflects the importance of fostering the emergence of HMT. The positive effects of teamwork, when compared to system use, do not only manifest in performative interaction outcomes (Walliser et al. 2019) but also humans' emergent states, such as system acceptance (Panganiban et al. 2020) and trust (McNeese et al. 2019). Yet, studies on HMT outcomes primarily embrace quantitative approaches, usually in private or military settings. There are, to the best of our knowledge, no qualitative inquiries to holistically capture the implications of HMT in organizations, despite the hypothesized wide-reaching implications (Seeber et al. 2020). Being aware of these newly emerging implications, i.e. understanding the teaming outcomes in an organizational context, is essential for organizations to be able to effectively leverage machine teammates (Jöhnk et al. 2021). Hereby, adopting a post-adoption perspective, especially in an explorative and qualitative way, allows us to learn from the intended and unintended teaming outcomes upon the integration of machine teammates. This, in turn, can be leveraged to inform the effective integration of machine teammates into other organizations and thus improve future teaming outcomes.

Category	Focus	Exemplary finding
Team formation	Investigations into the design of machine teammates for specific settings (e.g. Wiethof et al. 2021) and into machine configurations that foster teammate perceptions (e.g. Zhang et al. 2021)	Giving labels to teams, such as team 'red' and 'blue', fosters teammate perceptions (Johnson and Gardner 2007)
Teaming processes	Investigations into dedicated teamwork processes during the interaction (e.g. Walliser et al. 2019) and into potential (teamwork) roles machine teammates may qualify for (e.g. Siemon et al. 2020)	Team communication and coordination deteriorate when it is revealed that a team member is artificial (Musick et al. 2021)
Teaming outcomes	Investigations into performance-related outcomes as well as into outcomes in the form of humans' affective emergent states, such as trust (e.g. McNeese et al. 2019; Panganiban et al. 2020)	Voice- as opposed to text-based communication fosters HMT performance (Bogg et al. 2021)

Table 1. Research on machines as teammates

Socio-Technical-Systems Perspective

The STS perspective accounts for the evolving interdependencies of humans and technologies in modern organizations (Bostrom and Heinen 1977; Venkatesh et al. 2010). Hereby, it provides a critical view on the relationships emerging between people, technology, and outcomes to explain the behavior of organizational members. As illustrated in Figure 1, the STS perspective embraces the meaningful connection between technical systems, i.e. technological artifacts, and social systems, i.e. people and social relationships (Bostrom and Heinen 1977). These subsystems are jointly optimized and are interdependent parts in determining the success of the technology implementation (Venkatesh et al. 2010). In addition, STS also embrace the tasks that humans carry out with the IT artifact, the structures in which both subsystems interact, as well as the interaction context (in our study, the respective organization) (Venkatesh et al. 2010). Hereby, both, task and structure, are of relevance as influential factors in establishing the desired balance between the social and technical subsystem.

We leverage the STS perspective in our study as it presents a particularly valuable theoretical lens for inquiries into the integration of AI-enabled systems in organizations (Makarius et al. 2020; Niehaus and Wiesche 2021). Research stresses that not only instrumental but also humanistic outcomes should be considered upon the introduction of AI-enabled systems (Benbya et al. 2021; Riemer and Peter 2020). Humanistic outcomes are especially relevant in the context of machines as teammates due to the social nature of teamwork and the central role of humans (Memmert and Bittner 2022; Nass and Moon 2000; Seeber et al. 2020). As adopting the STS perspective facilitates the creation of socio-technical capital, allowing organizations to leverage machine teammates for a competitive advantage, it presents a suitable basis for inquiring into facilitators and inhibitors of integrating machine teammates (Makarius et al. 2020).

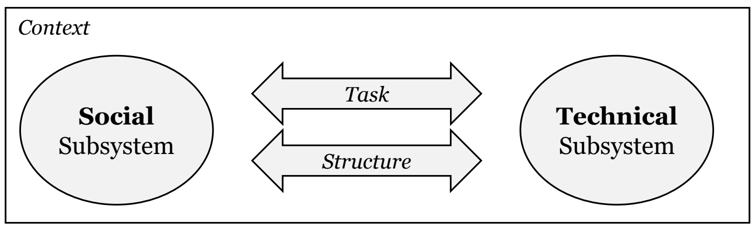

Figure 1. STS perspective on integrating AI-enabled systems in organizations based on Niehaus and Wiesche (2021)

Methodology

Due to the novelty of the 'machine as teammates' notion (Seeber et al. 2020), a qualitative, explorative research approach aimed at discovering novel perspectives instead of testing or extending theory is fitting (Corbin and Strauss 2008). Expert interviews are a fruitful research approach given the limited diffusion of performative AI-enabled systems and small teams working with them (Benbya et al. 2021; Jöhnk et al. 2021). Finally, as the content creation industry already employs mature performative systems, we focused on this industry to identify organizations leveraging machines as teammates (Memmert and Bittner 2022).

We used criterion sampling, a sub-form of purposeful sampling, to ensure that all interviewees meet the predefined criteria of importance (Patton 1990). To comply with our inclusion criteria, experts should have profound expertise in being part of or supervising a HMT situation fulfilling all prerequisites for HMT emergence as defined above. To identify suitable experts, we looked for content creation systems that could be leveraged as teammates. We identified three potentially suitable systems and conducted seven interviews with experts from the providers to ensure that the systems could be implemented as teammates. All systems embrace ML-based AI technologies in the form of Natural Language Generation and were sufficiently performative for HMT to manifest. In the case of system B, the interviews with provider experts also allowed valuable insights into working with the machine teammates based on long-term implementation projects the experts have accompanied. Integrating experts from providers further enriches the data by a multiple stakeholder perspective and supports triangulation (Gioia et al. 2013; Seppälä et al. 2021). To identify further experts, we contacted providers' clients via a direct reference. As a result, we recruited 25 more experts from organizations leveraging machine teammates for creating journalistic content or product descriptions. Both content types are of high strategical value to organizations: Creating journalistic content is the media industry's core business while product descriptions turned out as detrimental for time-to-market and return rates of products and are thus integral for performative outcomes. During the last three interviews, no additional insights regarding our research aim were revealed. Accordingly, we concluded that we had reached theoretical saturation and stopped acquiring new experts (Corbin and Strauss 2008; Gioia et al. 2013). Overall, the profound experience of our experts is not only reflected in our experts having an average of ten years of experience in the content creation industry. Further, experts had on average four years of experience in integrating these systems in organizations and working with them. Given the novelty of this new class of systems, the interviewees can thus be considered front-running knowledgeable agents and accordingly experts (Seppälä et al. 2021). Table 2 gives further details on our sample of experts.

ID	Org.	Type	System	Position*	ID	Org.	Type	System	Position*
E1	A	Provider	A	Top Management	**E17**	I	Provider	B	Team Lead
E2	B	User	A	Top Management	**E18**	I	Provider	B	Project Manager
E3	B	User	A	Project Manager	**E19**	I	Provider	B	Content Creator
E4	B	User	A	Content Creator	**E20**	I	Provider	B	Content Creator
E5	B	User	A	Content Creator	**E21**	J	User	B	Team Lead
E6	C	User	A	Editor in Chief	**E22**	K	User	B	Team Lead
E7	D	User	A	Top Management	**E23**	L	User	B	Content Creator
E8	E	User	A	Team Lead	**E24**	M	User	B	Content Creator
E9	E	User	A	Content Creator	**E25**	M	User	B	Top Management
E10	F	User	A	Content Creator	**E26**	N	User	B	Content Creator
E11	F	User	A	Content Creator	**E27**	O	User	B	Top Management
E12	G	User	A	Team Lead	**E28**	Q	User	B	Project Manager
E13	H	User	A	Team Lead	**E29**	R	User	B	Project Manager
E14	H	User	A	Content Creator	**E30**	S	User	C	Editor in Chief
E15	H	User	A	Content Creator	**E31**	S	User	C	Editor in Chief
E16	I	Provider	B	Top Management	**E32**	T	Provider	C	Project Manager

**Positions were pseudonymized to ensure anonymization*

Table 2. Experts who participated in this study

We collected the anonymous data via phone or video conferencing tools from October 2021 to February 2022. Interviews lasted on average 38 minutes. All of the interviews were conducted in German and excerpts were directly translated into English. We followed a semi-structured interview guideline, which embraced open-ended questions to allow experts to share their thoughts freely (Patton 1990). Before each interview, we briefly outlined the term and the concept of machines as teammates. We then proceeded with the four-section guideline, embracing i) experts' professional background and work, ii) the role and integration of the machine teammate, iii) the perception of the system as a teammate, including both positive and negative feelings, and iv) the impact of the integration of the machine teammate on the organization, such as concerning productivity or job satisfaction. The guideline was slightly adjusted during the interview process to incorporate the knowledge derived from previous interviews (Urquhart et al. 2010).

Following Saldaña (2009), we inductively analyzed the transcripts in two coding cycles in Atlas.ti. During the first cycle, we first leveraged (1) attribute coding for extracting information on experts and AI-enabled systems. Second, we used elemental codes in the form of (2) in-vivo codes, hence text passages with meaningful statements were used as codes for "breaking data apart and delineating concepts to stand for blocks of raw data" (Corbin and Strauss 2008, p. 195). We then engaged in (3) structural coding of these in-vivo codes, i.e. identified conceptual phrases that characterize a relevant topic to answering the underlying research question (Saldaña 2009). Structural coding is especially suitable for explorative investigations. It allows the delineation of insightful themes, such as 'feeling of helplessness' based on the statement "*you have the feeling you do not stand any chance at all to understand it*." We followed the recommendations for explorative inquiries by combining three coding methods and thus engaged in eclectic and iterative coding based on constant comparison (Saldaña 2009; Urquhart et al. 2010). During the second cycle, we applied (4) pattern coding to group codes according to commonality and superior meanings and to create mutually exclusive but collectively exhaustive categories (Saldaña 2009). As a result, we identified major categories, such as 'loss of control' by combining the themes 'heightened expectations' and 'higher pace of work.' The derived categories were then deductively clustered into the STS perspective as our analytical frame. Combining an analytical frame with explorative qualitative research has proven effective in describing novel phenomena in the IS discipline (Niehaus and Wiesche 2021). During the analysis, we employed several measures to ensure a rigorous and transparent process with trustworthy interpretations (Gioia et al. 2013). First, the analysis was discussed with another researcher as well as a student research assistant during both cycles of coding until consensus was reached, i.e. multi-researcher triangulation was applied. Second, the results were discussed with an expert in the field of interaction with AI-enabled systems. Third, secondary material was collected for triangulation purposes. We used press releases, white papers, case studies as well as material retrieved from experts, such as training documents and presentations. Fourth, we integrate direct quotes to give insights into experts' own terms.

Results

The insights from our interviews suggest that machine teammates are a worthwhile investment for organizations if implemented effectively, which underlines the relevance of our research question. The experts reached the consensus that machine teammates could not only be seen as a competitive advantage but would soon become essential to remain in competition and empower smaller organizations. The inductive analyses of factors for effective integration of machine teammates revealed six facilitating and seven inhibiting factors in the social and technical subsystem, as well as six influential factors in the task and structure dimension (see Figure 2). Subsequently, each factor is defined, the reasons for its emergence are explained, and finally, if addressed by experts, ways for leveraging or mitigating this factor are outlined.

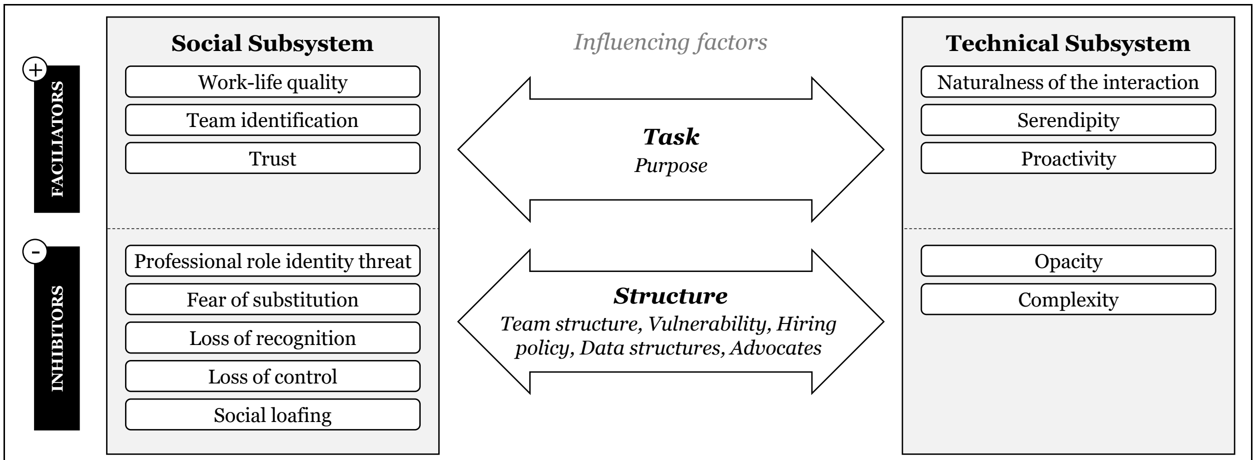

Figure 2. Factors to consider for effective integration of machine teammates

Social Subsystem

Regarding facilitators, first, fostering the objective **work-life quality** of employees facilitates the effective integration of machine teammates. Work-life quality refers to employees' perception of their work's enjoyability, for example with regard to work intensity as well as the opportunity to focus on intrinsically-motivated work. This work-life quality is, in turn, an important determinant of job satisfaction. Work-life quality can be fostered by freeing up employees of disliked and routine tasks upon the introduction of the machine teammate: "*They are super grateful because no one would want to sit down and write these Corona articles at 5 o'clock for all 420 counties*" (E3). Thus, machine teammates can be leveraged to create a more favorable work environment, which in turn positively affects work-life quality. Also, employees can focus on more value-creating and experimental tasks that correspond with their personal interests: "*You can focus on more complex, but also possibly more exciting topics, or just on something you prefer to write about*" (E3). Based hereon, employees assign a higher intrinsic value to their work and even perceive working with the machine as "*fun*" (E13). These positive effects of higher work-life quality can be leveraged by assigning the machine unenjoyable (routine) tasks while simultaneously creating the capacity for human team members to engage in value-creating tasks that correspond to their intrinsic motivation.

Second, **team identification** facilitates the integration of machine teammates in organizations. Team identification refers to human team members perceiving the machine teammate as a full-fledged teammate, instead of the machine being a teammate only per definition. For example, expert E3 states, "*I tend to consider it [a team member].*" Team identification fosters acceptance and, hereby, the willingness to engage with the machine teammate. The improved acceptance is evoked by the creation of an emotional bond when recognizing the machine as a teammate: *"I am already a bit emotionally attached to it*" (E3). The higher willingness to engage with the machine teammate is induced by recognizing the machine teammate as an agent: "*It is not only the system, it is much more*" (E6). Also, it makes humans more understanding and tolerant of mistakes, to a level similar as to human team members. The positive effects of team identification can be fostered by integrating the machine teammate in newly formed, small teams with at least two humans, framing it as work relief and integrating human-like attributes.

Third, **trust** in the machine teammate facilitates its effective integration. Trust fosters human team members' willingness to share work with the machine teammate without the urge to control each output: "*A certain amount of trust is a prerequisite, or it won't work*" (E30). The positive effects of trust can be induced by error-free performance, as otherwise "*trust is completely destroyed*" (E1). Also, awareness for the continuous learning of the system supports trust. The positive effects of trust usually emerge over time as humans get to know the machine teammate better. Experience makes humans aware of the machine's strengths and weaknesses, which experts describe as being analogous to the distinct areas of expertise of human colleagues. Hereby, the trust level should be similar to that in human colleagues: "*It's the same trust we have in editors. Because mistakes happen, things change all of a sudden, and people might not realize*" (E5). Thus, the machine teammate should be trusted, but not blindly. However, the statement "*I trust the system almost more than the colleagues*" (E3) suggests that overtrust may be an issue. Thus, organizations also need to ensure that employees are aware that the machine teammate's output should be challenged.

Regarding inhibitors, first, employees' perception of a **professional role identity threat** through the system hinders the effective integration of machine teammates. The professional role identity refers to employees' tendency to define themselves with their work and become firmly attached to how they have learned and practiced their work. The interviews revealed that human team members frequently saw their professional role identity threatened or disturbed, resulting in frustration and even employee turnover. Employees ask themselves whether "*it is still the work I want to do"* (E30). This frustration can result from employees being fond of and attached to the way they have practiced their work: "*They have been forced for years into a structure. So, after you have reluctantly gotten used to it, [management] says: Get creative again, after you haven't had opportunity for it for ages*" (E5). Further, employees being intrinsically interested in tasks that classify as routine, which machine teammates would usually take over, can evoke frustration. Expert E2 reports that colleagues are "*afraid that topics they have always written will be taken away from them*." The negative effects of a professional role identity threat can be mitigated by managers' careful analysis of established work patterns and changing them only after discussing the potential changes with the affected employees at an early stage.

Second, employees' **fear of substitution** hinders the effective integration of machine teammates. Fear of substitution refers to employees' fear of being let go because of the machine teammate. This threat leads to employees feeling anxious: "*Of course, it's not such a great prospect, because as a journalist you obviously think, "Hey, then I'll soon be out of the picture"*" (E32). Experts also describe it as the source of initial skepticism towards the machine teammate: "*We had massive problems with some people [...] of course, they were afraid for their jobs, for their future*" (E11). The perception that "*no one needs to fear their job*" (E24) can ultimately determine the success of the integration. This threat is also explicitly communicated: "*People came up to me and said, you're costing me my job. I am scared you're going to get me fired*" (E10). Aside from media-induced dystopia surrounding AI, the emergence of fear of substitution is fostered by employees witnessing the increased productivity of the machine teammate. Employees perceive it as competition: "*Editors notice that there is some kind of competition*" (E3). To mitigate the negative effects of fear of substitution, organizations should communicate that machines are "*an extension instead of a substitution*" (E21) and engage affected employees in the implementation "*as early as possible*" (E29).

Third, employees' **loss of recognition** negatively affects the effective integration of machine teammates. Employees' loss of recognition refers to human team members perceiving their own identity to fade and blurring into one identity with the machine teammate. Experts report that this raises resistance towards the machine teammate and fuels fear of substitution. Its emergence is fostered by employees receiving less recognition for output when working with the machine teammate as compared to before: "*I'd have to lie if I said: "Of course, the editor with his name up there gets just as much recognition"*" (E30). Instead of the recognition of the employee's efforts in engaging with the machine teammate, the machine teammate frequently takes the spotlight: "*When superiors exchange information among superiors, they say [system] is cool and so on and has made cool texts. But there's not much personal feedback, so if there is feedback, it's more attributable to the machine*" (E11). This may be rooted in management not being familiar with the respective contributions of the human and the machine: "*In fact, that's been a big problem that for a very long time we didn't get any recognition for what we were doing because people just didn't understand* *where it was coming from*" (E10). The negative effects of employees' loss of recognition can be mitigated by organizations establishing recognition structures that separately praise the human from machine team members and by encouraging employees to take pride in mastering the skillset for HMT.

Fourth, employees may be confronted with a **loss of control**, which also negatively impacts the integration. This notion refers to employees remarking a lack of control over the interaction and outcome. Experts report that this results in unease with the output generated by the team, increased cognitive load, and employees feeling "*exposed*" (E29). The increased scale of the output of the machine teammate, which does not always allow for manual control of every output, results in this unease with the output: "*We have to trust because we are not at all able to intercept everything and read everything*" (E10). This intensifies with the heightened expectations for humans: "*We come in with completely different quantities [...] We don't want to say that they should measure themselves against the machine, but actually want to measure the synergies*" (E5). Also, employees' cognitive load increases due to the higher pace of work due to the machine teammate: "*Now you need to react much quicker*" (E30). The feeling of being exposed to the machine also is described as one of the main sources of mistrust. To mitigate the negative effects of the loss of control, organizations should adjust the machine's pace and implement clear accountability structures.

Fifth, the emergence of **social loafing** can inhibit effective integration. Social loafing refers to team members exerting less effort in a team setting than when working individually. This results in deteriorating productivity and dysfunctional teaming. Experts suggest that the opportunity for social loafing is evoked by the drastic increase in output upon the introduction of HMT, whereby management often is not aware of the actual effort human team members need to put into creating the output. Thus, human team members can hide behind the output of the machine teammate and also use it as a scapegoat: "*And then you actually tend to blame the system, even though you realize that it is not responsible*" (E3). Further, experts report that human team members tend to become lenient when working with machine teammates and blindly trust their output to minimize effort. This can be tied to the disliked change in tasks upon the introduction of the machine teammate: "*This is just a job that - not meant to sound disrespectful - but that can be done by any intern who has a bit of skill and talent*" (E30). To prevent social loafing, organizations should create transparency over contributions, a clear responsibility structure, and set KPIs for each team member.

Technical Subsystem

Regarding facilitators, first, the **naturalness of the interaction** with the machine teammate helps its integration into an organization. The naturalness of the interaction refers to the intuitiveness and human-likeness of the interaction. Experts suggest that it increases affection for the machine teammate through relationship-building as well as the efficiency of interaction. It can further aid team identification: *"A team member is not necessarily characterized by his work, which he does, but by interaction. [...] Through human factors: emotions, exchange, something like that"* (E21). These positive effects can be leveraged by configuring the machine teammate for natural interaction. This embraces voice-based communication as well as the creation of a persona, including a name, a character, and emotions. Even merely a name can be powerful in creating a persona: "*We gave it a name, a human name, Anton. [...] I never got rid of this Anton. Everybody believes that we have a robot named Anton sitting here*" (E6). Then, naturalness also manifests in the machine teammate engaging in informal conversation: "*If I were able to tell it [...] that my child is now kind of starting to crawl. And it doesn't just say, "Oh, thank you, that's exciting information". But rather, it really gets into an exchange with me*" (E21). Last, the machine approaching humans with questions also fosters the naturalness of the interaction: "*I think that it could help if for example it approaches me with grammar questions and doesn't just pile up a log of error messages"* (E5).

Second, fostering **serendipity** of the machine teammate facilitates its integration into the organization. Serendipity refers to the machine teammate at times deviating from the expected to resemble human intuition: "*Serendipity is another magic word. That means we users want to not only get the standard displayed, but we want to discover new things, so you mix in something new every now and then*" (E31). According to experts, resembling serendipity in the machine teammate enhances the willingness to integrate the machine teammate into the team. Further, it helps to maintain the positive effect of the machine teammate on product quality, which may deteriorate when a filter bubble emerges: "*A stupid algorithm would at this point say: "He doesn't seem to be interested in that, I'm just not going to show it anymore" and create the famous bubble with it. To make sure that this doesn't happen, there's this principle of serendipity, and it's very important to me*" (E31). These positive effects can be leveraged by configuring the machine teammate to resemble serendipity. Experts suggest that this includes the machine teammate not only adhering to objective outcome measures, such as driving consumer engagement with "*clickbait content*" (E31) but also accounting for softer goals, such as the brand image. Machines' deviation off the maximizing choice based on quantitative analysis further helps prevent a filter bubble.

Third, **proactivity** of the machine teammate helps its integration. Proactivity refers to the machine giving "*input*" (E14), such as active suggestions and contributions aside from the output expected from the machine teammate. Experts suggest that proactivity fosters the effectiveness of the interaction, arising synergies, the feeling of team spirit, and the perception of flow while working. Also, it reinforces the perception of humanness and team identification with the machine. The positive effects of proactivity can, for one, be leveraged by the machine teammate making suggestions in the task conduct of human team members, such as suggesting an auto-completion of sentences or proactively highlighting interesting insights in data kept in legacy systems. Then, proactivity can manifest in the machine teammate highlighting errors of the human team members and making suggestions to resolve the errors: "*that it says proactively: "Hey, look, something here doesn't work or here, this works very well and could be used"*" (E19). Last, proactive analysis of the interaction can enhance the interaction effectiveness by highlighting unused functions: "*And that the machine then realizes "Okay, okay, you don't use this and that here very often". Maybe it could ask: "Do you know this function at all because you don't use it"*" (E3).

Regarding inhibitors, first, an inherent **opacity** to the machine teammate hinders its effective integration in the organization. Opacity refers to the commonly known "*black box character"* (E10) that AI capabilities bring, as the system's inner workings are often not explained. Opacity makes human team members uncomfortable when working with the system and creates mistrust. The negative effects of opacity can, according to the experts, be mitigated by explanations. Human team members do not generally oppose the conduct of the machine teammate, but rather want the opportunity to directly request an explanation like with human team members: "*The only difference is that you can talk to them and try to understand why the decision was made that way*" (E31). Experts highlight that explanations should not be integrated per default, as this may otherwise drive employees' cognitive load. The configuration of explanations is also detrimental. Explanations need to be understandable by all human team members, even without technological know-how. Otherwise, the transparency may backfire, and the perceived loss of control is fueled: "*Transparency for me means not only that the information is theoretically all accessible, but that it is also comprehensible. [...] If you throw explanations at me and say yes, you can look inside, this is how it works, [...], this is the mathematics behind it. That's mega transparent of you, but I just don't get it*" (E31). However, the need for explanations also varies with the machine teammate's complexity.

Second, the machine teammate's **complexity** negatively impacts teamwork with the machine teammate. The complexity of the systems refers to humans not being able to retrace the underlying reasons for the actions of a machine teammate. While complexity is closely related to opacity, it is more closely connected to human team members being overwhelmed by the information instead of wanting more information: "*At some point, I think one also feels overwhelmed. That is our experience. The more you put into it and the autonomous it gets, the more you move away from this classic writing work, and the higher the complexity becomes*" (E16). This can result in employees perceiving a feeling of helplessness, as they do not feel capable of understanding the new level of technological complexity: "*You feel so exposed because you have the feeling that you do not stand any chance at all to understand it*" (E31). The more complex the machine teammate becomes, the harder it also becomes to grasp the "*big picture*" (E31). To mitigate the negative effects of complexity, organizations should offer sufficient training to "*democratize the process in such a way that it is actually accessible to everyone*" (E18). Organizations should also carefully optimize the machine teammate's degree of autonomy and related complexity before implementing it.

Task

In line with the STS perspective, the task for which the social engages with the technical subsystem impacts the balance between the two subsystems. The **purpose** of the tasks the machine teammate is integrated for poses a significant influence. Task purpose refers to the goal of the tasks allocated to the integrated machine teammate. Two distinct purposes emerged from our interviews: complementary integration into extant tasks or extending the range of tasks performed. First, the allocated task to the machine teammate may follow the ulterior motive of complementing the work of human teammates, whereby usually existing work packages, such as routine tasks, are allocated to the machine teammate. This relieves human team members from undesirable work, allowing them to focus on their strengths. These synergies positively affect organizational performance, such as product quality. The machine teammate brings a fresh perspective: "*It helped me, in principle, to get a qualitative view of the data, which I simply didn't have before*" (E3). Further, the machine teammate challenges the potentially ineffective status quo of work routines. Integrating machine teammates with a complementary purpose further especially fosters work-life quality and team identification: "*That's why I tend to see it as a teammate [...] because it also does the work for us on weekends*" (E3). Second, in contrast, implementing machine teammates as additional manpower extends the tasks done in the organizations, whereby little to no work is relieved from human team members. Organizations' scale and scope of output are enhanced. Experts warn that this may come at the cost of hindering the emergence of facilitators (such as improved work-life quality) while at the same time fostering inhibitors (such as loss of control). Organizations may follow both purposes of task allocation at the same time. However, the positive effects of complementary integration should be leveraged, and the negative effects of increasing the scale of tasks carried out in an organization should be closely monitored.

Structure

Also, the structure in which the machine teammate is integrated is considered an influential factor in establishing the desired balance between the social and technical subsystems. As upon the integration of the machine teammate, "*many structures in the organization change*" (E16), designing these structural changes as effectively as possible has a strong impact. First, the **team structure** in which the machine teammate is integrated is an influential factor to consider. Positive effects emerge when a new team forms around the machine teammate. This enhances the team identification with the machine teammate: "*Without the machine teammate as a member of the team, the team would perhaps not exist at all [...] and therefore [it is] also the most important member of the team*" (E3). Second, organizations' **vulnerability** to the performance of the machine teammate presents an influential factor. Organizations become dependent on machine teammates' error-free performance: "*One is dependent on the system running. So, if it were to simply fail now, then our entire editorial team would be upside down for the time being, because no more texts would be published*" (E3). Further, organizations face a heightened risk of manipulation, as people may "*hack the system in some clever way*" (E31). Organizations can reduce vulnerability by implementing structures ensuring the availability of rapid tech support as well as strict IT security guidelines and tests. Third, the **hiring policy** is an influential factor. In-house hiring of specialized personnel for implementing machine teammates prevents the emergence of fear of substitution. It also allows maintaining existing job descriptions, thus reducing professional identity threats. Long-term, organizations should, instead of proactively letting employees go, prefer to reduce employee count by not re-filling positions that employees have left. Otherwise, employees' morale can be damaged and fear can be fostered. Fourth, suitable **data structures** are an important influence. Even though the machine teammates will need even less structured data in the future, the correctness of the input data is critical for the successful integration of the machine teammate. The availability of suitable data is one of the most considerable obstacles before integrating the machine teammate. Last, appointing **advocates**, such as in the form of lead users, can be very influential. Advocates can significantly reduce skepticism towards machine teammates, reduce employees' fear of substitution, and support integration success: "*There was [name redacted], who was very much behind. She fought like a lion to make sure we didn't jump ship*" (E8). In summary, these structure- as well as task-related influential factors can tip the balance between the social and technical subsystem and are thus also integral for effective integration of machine teammates.

Paradoxical Interrelatedness of Factors

While the facilitators and inhibitors revealed in this study are presented as separate entities, their interrelatedness should not be disregarded. We revealed relationships within the dimensions of facilitators and inhibitors, such as by highlighting the relationship between team identification and naturalness of interaction or loss of recognition and fear of substitution. However, our field insights further suggest that the seemingly positive effects brought about by facilitating factors can also be associated with negative, contradictory effects. More specifically, inadvertent paradoxical effects between facilitators and inhibitors can emerge. Hereby, paradoxical effects refer to a state in which fostering a positive concept (e.g. facilitator) unintentionally leads to the emergence of a negative concept (e.g. inhibitor) (Seeber et al. 2020). Thus, facilitators of introducing machine teammates can exhibit the self-contradictory nature of paradoxes. The revealed paradoxical effects are illustrated in Figure 3 and are elaborated in further detail subsequently.

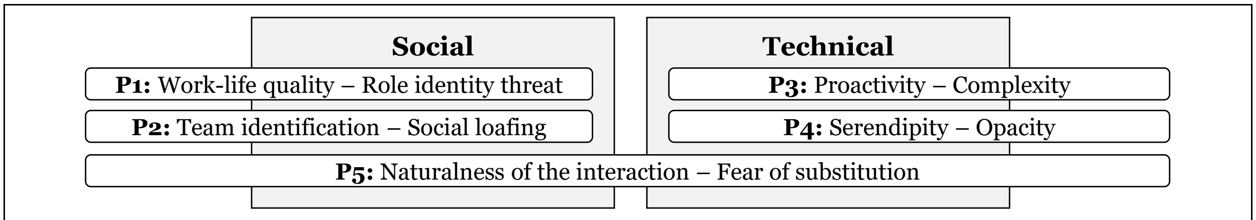

Figure 3. Paradoxical effects within and across subsystems

Within the social subsystem, first, a paradoxical effect between improved work-life quality and professional role identity threat emerges. The objective work-life quality of employees is improved by relieving employees of mundane tasks, leaving room for higher-value work, such as more creative tasks (Seiffer et al. 2021). While the logical consequence would be that employees' job satisfaction is improved by fostering objective work-life quality (Riemer and Peter 2020), experts indicated that not all employees were fond of this change, as some were comfortable with mundane tasks they got used to or had a personal interest in areas considered undesirable by other employees. Thus, even though the machine teammate can empower employees, organizations need to be aware that not all employees want to be empowered and strive for complex work, as also suggested by Riemer and Peter (2020). Therefore, the facilitating effect of improving the work-life quality may be undermined by the emergence of professional role identity threat. Another paradoxical effect in the social subsystem manifests between team identification and social loafing. Despite its positive effects, team identification can induce social loafing. When humans recognize the machine as a teammate, they may feel that they are not solitarily responsible for the team outcome - in contrast to when they are only augmented and retain full responsibility. In line with this, research suggests that this over-reliance on the machine teammate may result in a loss of unique human knowledge in the form of wisdom of crowds (Fügener et al. 2021). Thus, our insights suggest that when the machine is considered a team member, the productivity and contribution of human team members need to be closely monitored.

Within the technical subsystem, a paradoxical effect manifests between the configurations of proactivity and complexity. While proactivity is desirable for the machine teammate, experts often mentioned that the complexity that may emerge with this proactivity needs to be closely monitored. Thus, organizations face a trade-off between more proactive, and thus more effective, machine teammates and more complex teammates, which may increase employees' helplessness and cognitive load. The concept of proactivity is closely related to the degree of automation. Hereby, similar to the revealed paradox, individuals' preference for automation of advisory systems takes a U-shaped relationship (Rühr 2020). A dilemma manifests, as higher levels of automation lead to improved performance, but users of the system fear not being able to manage the complexity arising from it. Another paradoxical effect manifests between serendipity and opacity. Serendipity encompasses the machine teammate deviating from the expected. Research on advisory systems promises a richer and more engaging experience upon implementation of serendipity (Cui et al. 2021). Yet, experts highlight that serendipity comes at the cost of making it harder for humans to understand the rationale of the machine teammate. While opacity is not as relevant in the consumer recommendation context (Cui et al. 2021), it is highly relevant for machine teammates that are attributed a great deal of responsibility in organizations. Accordingly, organizations need to identify suitable explanation strategies for their machine teammates to mitigate the potential negative effects of serendipity.

A fifth paradoxical effect manifests between the machine teammate's naturalness of interaction and employees' fear of substitution, thus between the social and technical subsystem. While the majority of our experts suggest that higher naturalness of interaction increases performative and affective outcomes, some stress that the humanness associated with naturalness is not desirable or only so in a "*leisure context*" (E4). According to our experts, non-human-like machine teammates create a greater distance between human and machine team members. Experts suggest that this distance maintains human employees' perceived right for existence in the organization. Also, extant research suggests that humans feel threatened by natural interactivity (Rzepka and Berger 2018). This is even accelerated in the organizational context, as humans fear for their livelihoods. Accordingly, organizations need to account for the negative effects of natural interactivity, such as by clear accountability and recognition structures. Overall, the emergence of these paradoxical effects, i.e. unintended consequences upon the introduction of machine teammates, was already suspected in theory (Raisch and Krakowski 2021). By empirically revealing these effects, we are able to "shed light on the relevance of these ambivalent effects in practice" (Seeber et al. 2020, p. 9).

Discussion

In this study, we analyze how the human team members of a human-machine team have experienced the integration of a machine teammate into their organization. We leveraged the STS perspective to ensure a holistic view. We derived six facilitators and seven inhibitors of effective integration of machine teammates across the social and technical subsystems. We further revealed six influential factors in the task and structure dimensions. In addition, our insights suggest paradoxical interrelationships between some factors, highlighting potential unintended consequences that facilitators may inadvertently trigger. While not all facilitators and inhibitors are equally relevant to each organization, our insights provide an explorative account of potentials and problems that can guide the introduction of machine teammates.

Yet, the specificities of the investigated context in this study, performative systems for content creation purposes, should also be considered. In content creation, machines take over tasks considered innately human, as writing is associated with human wit and creativity and can be considered a subjective task. Algorithm aversion is accelerated in subjective application contexts, as algorithms are considered more capable in exclusively objective application contexts (Jussupow et al. 2020). Thus, in the case of content creation, human team members' skepticism, resistance, and threat may be higher than in the case of machine teammates taking over strenuous, objective physical tasks, such as fabric robots. Yet, it is interesting that even though content creation is innately creative, and thus employees specialized in this field should thrive for being able to perform creative work, our experts report that employees are frustrated with being empowered to more creative, and thus complex, work. This suggests that the relevance of the paradox surrounding work-life quality and professional role identity threat may even be magnified in the context of other industries or less creative fields of work. Accordingly, the application context may reduce or accelerate the magnitude and relevance of facilitators and inhibitors of integrating machine teammates.

Regardless of these considerations, our insights can be used to deduce the relevance of separately inquiring into machines as teammates. This relevance can be highlighted by comparing our insights to insights from the traditional form of interaction explored in the IS domain, system use. Two lines of research on AI-enabled system use emerge as closest to our study: organizational implementation of AI-enabled advisory systems as well as substitutive cognitive automation. Machine teammates set themselves apart as they can be positioned at the intersection of augmentation (the goal of advisory systems) and automation (the goal of substitutive cognitive automation) (Raisch and Krakowski 2021). In the following, we draw on research on these two system types as well as human teams to highlight distinctive phenomena of the HMT context.

Based on our insights, factors can be delineated that newly emerge upon HMT instead of system use. Regarding the social subsystem, team identification emerges only in the context of HMT. This team identification effectively enhances performative and affective outcomes (Walliser et al. 2019). Hereby, the positive effects may be attributed to social facilitation. This concept originates in teaming research and refers to humans performing better in the presence of other humans (Zajonc 1965). As upon team identification, the human recognizes the agentic nature of the machine teammate, social facilitation may manifest, and humans' performance may improve. Another concept associated with team identification is the emergence of team cohesion, one of the most significant drivers of the superiority of teamwork over groupwork (Kozlowski and Ilgen 2006). These teaming-related outcomes set HMT apart from system use. Further, social loafing, a concept from human teaming, only emerges in the HMT but not system use context. In system use scenarios, humans are usually only supported by the system. Hence, humans need to perform actions themselves and cannot hide behind the system. Due to the intertwined nature of HMT, it is harder to disentangle machine and human conduct, fostering the emergence of social loafing. Interestingly, extant quantitative research suggests social loafing does not manifest in HMT (Siemon and Wank 2021). Yet, the experiment could only operationalize working with the machine teammate for a short period, and only half of the participants identified the machine as a teammate (Siemon and Wank 2021). As also shown by human teaming research, social loafing does not necessarily appear when the team starts working together but may emerge over time (Karau and Williams 1993). Thus, upon team identification and a long period of working together, social loafing can emerge in HMT but is unlikely to emerge in system use scenarios. The entanglement of humans and machines is also closely tied to a perceived loss of recognition. The root cause of it may be delineated from social comparison theory, which denotes that human team members determine their own perceived worth based on the comparison to other team members (El-Shinnawy and Vinze 1998). As the machine teammate is perceived as a separate agentic entity in the team rather than an extension of the human team member (Baird and Maruping 2021), witnessing the machine teammate creating a much larger scale of output may be frustrating to humans. As this phenomenon builds on the machine teammate's agentic nature, it is unlikely to manifest in a use scenario.

Aside from these newly emerging phenomena, some phenomena also become more pronounced in the context of HMT. Regarding the social subsystem, work-life quality is more significantly improved in a HMT context, as the machine teammates can take over complex tasks instead of only supporting humans in task conduct and automating simple tasks (Engel et al. 2021). This leaves more room for empowerment than sole advisory system use or substitutive automation contexts (Riemer and Peter 2020). Yet, also employees' fear of substitution is accelerated by the performative nature of machine teammates. As the human team members are technically only contributing a fraction of the output of the machine teammate, the fear of substitution reaches a new scale in HMT compared to advisory system use contexts (Mirbabaie et al. 2022; Rzepka and Berger 2018). This fear can also embrace the potential loss of status position within the organization (Mirbabaie et al. 2022). Further, the perception of a loss of control becomes more pronounced in HMT. While in the context of advisory systems, the human stays in control and is accountable, humans are forced to give up greater degrees of control in HMT. In a teaming setting, the human team members are held equally accountable for the team's outcomes. Hereby, the output of the machine teammates is also usually complex. In contrast, substitutive automation mostly follows a rule-based approach, and humans are not held accountable for the performance of the automation. Regarding the technical subsystem, opacity is more pronounced in a HMT setting given machine teammates' performative nature and inherent complexity. In an organizational context, mechanisms to alleviate opacity, mainly explanations, become even more relevant. Yet, extant research mainly focuses on explainable AI for advisory systems (Jussupow et al. 2020). Features relevant in the advisory context, such as whether DSS should proactively reveal their recommendations, are not relevant for performative systems, such as in the HMT context. Other notions, such as indicating error boundaries, are, in contrast, also relevant in the HMT context (Bansal et al. 2021). Accordingly, research needs to identify novel, suitable explanation strategies for machine teammates.

The remaining phenomena are equally relevant in the HMT and system use context. For example, the manifestation of professional role identity threat due to a change in tasks upon introducing AI-enabled systems is not new (Mirbabaie et al. 2022; Strich et al. 2021). While the complementary and empowering nature inherent to HMT could suggest that HMT may alleviate these concerns, our study suggests otherwise by revealing it as a central inhibitor. While all outlined phenomena warrant interesting insights, especially those that newly emerge or become more pronounced require further research. The phenomena of team identification, social loafing, and loss of recognition newly emerge given HMT, while the phenomena of improved work-life quality, fear of substitution, loss of control, and opacity are magnified in HMT.

Contribution, Limitations, and Future Work

Regarding the theoretical contribution, this study, first of all, extends the research on AI in organizations by contributing to the post-adoption perspective. Due to the pilot character of many AI projects, qualitative research on the effects of the integration of performative AI-enabled systems is scarce (Jöhnk et al. 2021). Yet, performative systems bear fundamental changes to the organizations they are implemented in (Benbya et al. 2021) and can break down the artificial separation of the automation versus augmentation nature (Raisch and Krakowski 2021). Accordingly, we provide early insights into the organizational application of performative systems at the intersection of automation and augmentation. Second, we contribute to a call for research for inquiring into organizational integration of machine teammates (Seeber et al. 2020). HMT is especially valuable to organizations, as it significantly improves performative and affective outcomes as compared to system use (Walliser et al. 2019). Our explorative inquiry into teaming outcomes, an area so far dominated by quantitative work, significantly extends the understanding of the novel phenomenon of HMT. Our insights on facilitators and inhibitors and their (paradoxical) interrelationships further advance the research on leveraging the potential of machines as teammates in organizations. Third, our study extends the research stream on the emergence of bi-directional interaction enabled by the progress in AI (Diederich et al. 2022; Schuetz and Venkatesh 2020) and aids the theorizing on the 'next generation of use' that currently prevails in the IS discipline (Baird and Maruping 2021; Baskerville et al. 2020). Hereby, HMT presents a worthwhile manifestation of the novel forms of interaction (Rix 2022). By differentiating the organizational impact of HMT from insights on the impact of traditional IS research, we critically assess distinctive and novel phenomena that emerge given increasingly collaborative and agentic systems while at the same time highlighting concepts that may remain of similar relevance. Our insights underline the importance of new theorizing given this next generation of systems (Schuetz and Venkatesh 2020).

Regarding the practical contributions, we first raise awareness for the emergence of a new form of interaction between employees and machines. Organizations need to be aware that machines move from an advisory to a performative role and that this shift has important organizational implications. By leveraging a post-adoption perspective on the consequences of introducing machines as newly found teammates, we make managers aware of how this situation is different from employees interacting with systems traditionally researched in IS, such as DSS. Thus, enabling managers to recognize such a new form of interaction is a valuable practical contribution, as managers will need to anticipate different implications and proactively manage them. Second, by relying on the STS perspective, we further raise awareness that managers should not only focus on optimizing the IT artifact, hence the technical subsystem, but also need to maintain a balance with the social subsystem to ensure successful integration of machine teammates. As shown in the paradoxical interrelationships, manipulating a technical aspect, such as the naturalness of the interaction, may have unexpected repercussions on the social subsystems, such as by employees feeling fearful of substitution. By highlighting the connections between the subsystems, but also pointing out influential factors in the task and structure dimensions, we stress managers to consider the holistic picture. Third, our study gives organizations that plan to leverage machine teammates an insight into specific facilitating and inhibiting factors. We give actionable and specific recommendations how facilitators can be fostered and inhibitors can be counter-acted, such as by highlighting that transparent responsibility structures are required to ensure employees are not suffering from a loss of control or start social loafing.

Despite a high degree of rigor in conducting our research, this study is not without limitations. First, given the limited diffusion of machine teammates, our study focuses on the content creation context. Despite our critical reflection, the generalizability of our insights needs to be validated in other contexts. Especially the relevance of the paradoxical interrelationships could be context-dependent, urging for follow-up work. Second, we only focus on cognitive systems. Embodied systems, such as factory robots, may provide different implications and thus require further research (Rix 2022). Third, while the systems in our sample share many commonalities, their degree of autonomy slightly differs. Yet, we did not inquire into these differences. Future research might explicitly analyze machine teammates at different levels of autonomy. Fourth, there is no one universal definition for when tools become teammates. We base our sample selection on an aggregated definition based on extant literature. There are first attempts at defining HMT, such as identifying drivers of the team formation perception or design principles for machines to become teammates in a specific context (Rix 2022; Wiethof et al. 2021). Yet, as these studies provide no definite answer, future research should empirically derive minimum prerequisites for the positive effects of HMT to arise. In addition to the research impulses raised by the limitations, a large-scale survey study could be used to analyze the significance of each of the identified phenomena as well as the paradoxical interrelationships. Also, inquiring into the impact of each of the factors on team dynamics or effectiveness constructs, such as team identification and resilience, could be worthwhile (Kozlowski and Ilgen 2006).

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