# Beyond the Dichotomy of Tool vs. Teammate: Functional, Normative, and Experiential Perspectives on AI in Organizations

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**The dichotomous debate coined "Team member vs. Tool" addresses the question of whether artificial intelligence (AI) is, can, or should be a team member or a tool in an organizational context. In this paper, we challenge the assumption that the "Team member vs. Tool" positions are in tension at all and posit that apparent discrepancies between these two positions mainly arise from a failure to distinguish between different analytical levels: functional descriptions of what AI does, normative claims about what AI should be, and social-psychological accounts of how people experience and interpret AI at work. We disentangle these three perspectives and their respective contributions to the conceptualization of AI in the work and organizational context. Building on this distinction, we further demonstrate that the relations between these perspectives are interdependent but asymmetrical. Functional properties of AI systems more directly shape social–psychological experiences, which in turn inform organizational practices, while normative perspectives primarily influence both functional design and interpretive frames through processes of translation and implementation. We argue that many tensions in the literature stem from overlooking these uneven pathways of influence.**

*Artificial Intelligence, Conversational Agent, Metaphor, Work Design*

## 1. INTRODUCTION

Imagine forty years ago, claiming that one had "teamed up" with a telephone or a fax machine to achieve a goal such as acquiring new clients would likely have raised an eyebrow. These technologies were and are tools that people operate with. They mediate work processes, but they are not perceived as collaborators, colleagues, or teammates. The introduction of personal computers began to challenge this purely instrumental perspective. Although interaction with computers largely remained task-oriented, these systems appeared complex and intelligent to many

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users. As a result, tendencies to anthropomorphize computers and to treat them as social actors became apparent and have shaped research for decades (Nass et al. 1996).

Fast forward to the current Artificial Intelligence (AI) era, the landscape of work appears remarkably different. While the idea of teaming up with AI still invokes skepticism (Evans et al. 2025), it is no longer particularly surprising. Companies around the world have successfully re-branded formerly servile digital assistants as team members operating at eye level, for example, through labels such as co-pilot or companion. Through such marketing narratives, but also organizational strategies, and everyday workplace discourse, this humanization has become linguistically and organizationally plausible.

At the same time, research in work and organizational psychology in this area is growing, particularly in understanding how the collaboration between humans and AI systems evolves over time and which psychological and social dynamics are involved. The focus lies on the purpose, scope, and tasks of AI systems and how these are communicated, designed, and implemented into work tasks and processes to support not only productivity and innovation but also employee and team well-being and job satisfaction (Selenko et al. 2022; Ulfert et al. 2024). Despite these efforts, existing work remains scattered due to conceptual confusion and lack of a common foundation, thus risking jangle-fallacies, whereby similar phenomena are addressed under divergent terminologies, complicating interdisciplinary exchange and the integration of empirical findings (Berretta et al. 2023; Flake and Fried 2020). To move forward, we, as researchers, need a clear shared understanding of this human-AI collaboration and a clear starting point to theoretically and empirically contribute to human-centered, ethical, and sustainable jobs and organizations in tomorrow's world of work.

In this conceptual work, we argue that one of the main reasons for this scattered and emerging field is that collaboration between humans and AI systems is underlined by a demanding, dichotomous, and normatively loaded debate about whether AI can function as a team member or whether it is a tool. This debate refers to AI in the form of cognitive agents, that is, artificial entities, run on machine learning or AI techniques, which enable them to perform complex tasks that otherwise require higher cognitive abilities (Dastani and van der Torre 2019). In the modern workplace, such cognitive agents promise to seamlessly blend human expertise with machine intelligence (Bankins et al. 2024). This most often includes generative AI systems (genAI), which are AI models that are trained on large data sets and are capable of independently generating text, images, or music based on training data (Bubeck et al. 2023). Large language models (LLMs) in particular, which are language models trained on unmarked text data using neural networks, are likely to be regarded as team members (Li et al. 2025).

Some researchers argue that their integration into human–AI collaboration mirrors core features of traditional teamwork, thereby justifying the attribution of social roles and team processes to AI systems (Siemon 2022; Stowers et al. 2021). Namely, they define and investigate AI team members as cognitive agents that have unique team roles, contribute to team performance, are part of the joint team activities and responsibilities (Georganta and Ulfert 2024). Others argue that cognitive agents should be conceptualized and understood as tools, arguing that AI as tools are cognitive agents that support humans in task execution but do not participate as autonomous agents in team processes (Shneiderman 2020). Multiple papers address the tool vs. team member debate (e.g., (Naikar et al. 2025; Rix 2022) and/ or introduce other metaphors (especially for generative AI systems) such as AI as a "sparring partner" (Herrmann 2025), AI as a "sidekick" (Bruni et al. 2023), AI as a "butler" (Chen et al. 2024) or through "human-animal teaming" (Lum and Phillips 2024).

We note that, in this paper, we use the term "metaphor" broadly to refer to linguistic and conceptual framings through which AI systems are understood, designed, and experienced in organizational contexts. Our interest is therefore not in metaphor as a purely linguistic phenomenon, but in how such framings shape assumptions about system functionality, responsibility, interaction, and appropriate forms of human–AI collaboration.

To that end, the aim of this conceptual article is to contribute conceptual clarity and offer a clear starting point for researchers on human-AI interaction, collaboration, and teaming. To achieve that, we do not add weight to either the "AI as team member" nor the "AI as tool" positions, but instead challenge the assumption that these positions are in tension at all. We argue that the apparent discrepancy arises from a failure to distinguish between analytical levels: functional descriptions of what AI does, normative claims about what AI should be, and social-psychological accounts of how people experience and interpret AI at work. By disentangling these levels, we show that the "team member vs. tool debate" and other related metaphors lose significance. We further call on researchers in work and organizational psychology to critically

reflect on whether their theoretical contributions are examining people's perceptions, expectations, and lived experiences of working with AI, rather than in attributing social or moral status to technical systems.

The conceptual perspectives presented in this paper emerged from a transdisciplinary workshop on human-AI teaming, during which we critically engaged with the ongoing "team versus toolmate" debate. Rather than offering a systematic or comprehensive review of the literature, this concept paper synthesises the insights generated through these collaborative discussions. As such, it should be understood as a pre-empirical, exploratory, and deliberately non-systematic conceptual contribution that aims to structure the debate, identify key tensions, and stimulate future empirical and theoretical research.

## 2. BACKGROUND

Before we review both the "AI-as-tool" as well as "AI-as-team-member" metaphors, we briefly want to emphasize that how we describe these technologies is consequential. Research from various fields has long studied the relationship between language production and the way we think, suggesting that language influences a speaker's worldview and cognition (Winawer et al. 2007; Boroditsky 2001; Lakoff and Johnson 2024; Brugman et al. 2019). In short, there is, by now, ample evidence that how we talk about the world matters (Gupta et al. 2024; Langer et al. 2022; Inie et al. 2024; Mitchell 2024; Wischnewski and Nguyen 2026).

Moreover, following previous works (Schmutz et al. 2024), for the analysis below, we use "teaming" to refer to forms of interdependent coordination characterized by shared goals, reciprocal adaptation, and dynamic role allocation.

### 2.1. The Instrumental Side: AI as a Tool

From early manual tools to modern computational systems, technological artifacts have traditionally been conceptualized as tools, that is, means through which human agents pursue their goals. To that end, humans have long relied on tools to extend their physical and cognitive capabilities. With the growing digitization and the ongoing technological progress, many tools transitioned from being manually operated to being partially or fully automated, giving rise to extensive research on human–automation interaction (Janssen et al. 2019). As such, technological systems were still primarily conceptualized as instruments that execute predefined functions under human control or supervision, reinforcing the view of technology as a functional tool rather than a collaborative partner (Parasuraman et al. 2000).

From this perspective, conceptualizing AI as a tool is commonly associated with several advantages. A central argument is that the tool metaphor helps prevent exaggerated expectations toward AI-based technological systems. By framing AI as a supportive instrument, it emphasizes the primacy of human agency and control and underlines that humans remain the responsible actors in work systems, while AI only serves as a means of support (Naikar et al. 2025). This view aligns with calls to preserve human creativity, ethical reasoning, and domain expertise, and to maintain human self-efficacy and sense of meaningfulness (Shneiderman 2022). Moreover, the tool metaphor mitigates risks associated with anthropomorphism, i.e., the tendency to attribute human-like intentions, emotions, or social capabilities to technical systems (Epley et al. 2007). As AI systems do not possess intentions, understanding, or social competence in a human sense, framing them as tools helps to avoid the development of inappropriate perceptions of social connection or relational closeness and the likelihood of unrealistic expectations that may arise when automated behavior is interpreted as intentional or socially grounded (Akbulut et al. 2024).

However, referring to AI as a tool is not without critique (Laba 2025; van Biezen 2025). One unresolved issue concerns what it actually means to conceptualize AI as a tool in the context of contemporary, adaptive systems. As AI systems gain autonomy, exhibit agent-like behavior, and develop persistent dependencies with human users, the applicability of a purely instrumental tool framing becomes increasingly ambiguous (Naikar et al. 2025; Jiang et al. 2023). In such settings, AI systems no longer merely execute predefined functions but actively shape decision-making, workflows, and outcomes. These dynamics challenge a strict tool-based perspective and raise questions about whether the instrumental metaphor can adequately capture the evolving nature of human-AI interaction. Importantly, this critique does not reject the instrumental assumptions in general; rather, it highlights the need to specify the frontiers of the tool metaphor and to complement it with approaches that account for expanding system capabilities, increasing interdependencies, and emerging forms of joint activity between humans and AI systems.

Moreover, for the context of creative industries, Laba (2025) argues that this metaphor inadequately captures the sociotechnical and cultural dynamics through which contemporary AI systems operate. The paper contends that framing AI as a neutral

instrument suggests that these systems function simply as extensions of human intention, thereby obscuring the broader networks of economic interests, institutional practices, and ideological commitments embedded in their development and deployment.

### 2.2. The Social Side: AI as a Team Member

The explicit emergence of the teaming metaphor in research occurred primarily within human factors and human-robot interaction research. Work on human-autonomy teaming argued that highly autonomous systems should be conceptualized as participants in joint activity, characterized by interdependence, coordination, and shared goals rather than simple command-execution relationships (Johnson et al. 2018; Seeber et al. 2020). This marked a conceptual shift from automation toward collaboration.

Building on this foundation, the term human-AI teaming gained prominence as AI systems became more interactive, adaptive, and socially embedded. Human-AI teaming has been defined as a process in which one or more humans collaborate with one or more fully or at least partially autonomous AI systems. Both have different and complementary capabilities and work together to achieve a common goal (Berretta et al. 2023). During this process, the roles of the team members adapt dynamically, which requires mutual cooperation, communication, shared interests, shared situational awareness, shared mental models, and trust within the team (Berretta et al. 2023; Hagemann et al. 2023).

The teaming metaphor is recently gaining traction because it allows to align research on human-AI collaboration with established teamwork theories and provides a language that captures the dynamic and interdependent nature of contemporary human-AI systems, without necessarily implying that AI possesses human-like social or moral properties. Researchers increasingly adopted concepts from team and organizational psychology, such as shared mental models, trust, communication, and role allocation, to describe human-AI interaction (O'Neill et al. 2022; Teaming 2022; Seeber et al. 2020). As such, considering humans and AI as a team is considered helpful as it draws attention to the value of team interactions and interrelated needs of human team members (National Academies of Sciences and Engineering and Medicine 2021). In line with this, empirical work has shown that some (in human teaming research well established) teamwork concepts are significantly altered in human-AI teams, i.e., communication or coordination (Zercher et al. 2023) or team cohesion (Rieth et al. 2026).

Another argument from researchers applying the teaming metaphor is that with increasing technological capabilities, AI will develop more and more "teammate-like skills" (Naikar et al. 2025). Theoretical models, such as the "autonomous agent teammate-likeness" (AAT) by Wynne and Lyons (2018) postulate that with increasing degrees of agency, synchrony, benevolence, communication richness, interdependence, and team-focus AI systems will appear more teammate-like. Unlike conventional technologies, AI can engage in diverse tasks with varying autonomy, working with people in interrelated workflows (Kozlowski and Ilgen 2006). Researchers explain their viewpoint on an AI team member by responsibilities and interactions rather than technical features (Georganta and Ulfert 2024).

These arguments can hold significant implications not only for how research is conducted on human-AI collaboration, but on how AI is designed and implemented: First, it can be construed as a call to developers to develop machines as human-like as possible, e.g., regarding their appearance, communication, or cooperation style. Second, it can be understood as an aspiration to make the use of AI in work teams seamlessly in terms of its disruptions on teamwork processes and states (Naikar et al. 2025).

At the same time, the teaming metaphor has also been met with substantial criticism, and framing AI as a team member has been considered inappropriate or even potentially harmful. A prominent critique of framing AI as a team member centers on the fundamental mismatch between human social properties and the capabilities of AI systems (Naikar et al. 2025), famously summarized by Shneiderman as "computers are not people and people are not computers" as they lack e.g., responsibility or creativity (Shneiderman 2020). Scientists across disciplines see a risk in forcing human-centered theories of teamwork onto systems that cannot meaningfully satisfy this assumptions (Evans et al. 2025).

Beyond the theoretical concerns, the team member metaphor can amplify hype and inflated expectations that already come along with AI systems. By anthropomorphizes AI, people might develop unrealistic expectations regarding a system's capabilities, e.g, in regard to its performance; (Zhang et al. 2021). In this sense, the metaphor is not merely inaccurate, it actively shapes perceptions that might be detrimental, i.e., if people expect "an ideal human" (Zhang et al. 2021), thereby attributing too much trust in - potentially false - outputs, leading to overtrust (Wischnewski et al. 2023). This is in line with work that finds metaphors that signal high competence

of AI systems to attract new users, meaning that people prefer to try out a system that is described with a metaphor that signals high competence (e.g., ´´executive" rather than ´´toddler") but that user evaluation after actual system use is more favorable for systems described by less competent metaphors (Khadpe et al. 2020). Conceptualizing AI as a team member can further lead to increased job insecurity and thus reduce intended adoption by employees, particularly when AI systems are presented as holding greater responsibility for shared tasks (Flathmann et al. 2024).

### 2.3. Bridging the Social and Functional Side: A matter of perspective

The outlined debate demonstrates that neither the "AI as team member" nor the "AI as tool" perspective can be outright dismissed as both offer meaningful insights while simultaneously raising (different) theoretical, practical, and ethical concerns.

In the following, we argue that by anchoring the arguments of both sides in three different, interrelated perspectives, discrepancies disappear, and the perceived tension between the debates can be united. We suggest that discrepancies stem from three fundamentally different analytical angles with which researchers look at the "team member vs. tool" debate: (1) a functional perspective concerned with what AI technically functionalities, (2) a normative perspective addressing what AI should be in light of ethical, legal, and philosophical considerations, and (3) a social–psychological perspective focusing on how people actually perceive and interact with AI systems (see Figure 1).

We do not propose these perspectives as an exhaustive ontology of human–AI collaboration. Rather, they represent three recurring forms of claims that underpin the contemporary "tool versus teammate" debate. Across the literature, arguments typically concern one of three questions: what AI systems are capable of performing (functional perspective), what role they ought to have in organizations (normative perspective), or how they are perceived and experienced by people in practice (social–psychological perspective). While additional perspectives, for example, economic, legal, or organizational analyses, may provide valuable insights, they generally contribute to or operate within one or more of these broader analytical perspectives. Our framework, therefore, aims not to classify every aspect of AI in organizations, but to distinguish the principal types of claims that are frequently conflated in discussions of human–AI collaboration.

In addition, our framework follows the premise that AI in organizations is best understood as part of a *sociotechnical system* (Appelbaum 1997), where technical characteristics of AI systems (functional perspective) are shaped by the ways in which these systems are perceived and enacted by people in practice (social-psychological perspective). However, contemporary AI is also increasingly shaped by explicit ethical principles, organizational policies, and regulatory requirements. We therefore distinguish the third, normative perspective that captures prescriptive claims about how human–AI interactions ought to be designed and governed. Together, these three perspectives provide a holistic analytical lens for examining AI in organizational contexts while avoiding the conflation of descriptive, experiential, and prescriptive claims.

### 2.4. (1) Functional: What is AI?

Part of the discussion stems from a technological viewpoint (typically driven from computer sciences/ engineering) that focus on system capabilities, autonomy, appearance and task scope. A key question from this position is: What does the system technically do and how does it appear? Aspirations to design (and market) AI "team member like" might arise from the goal to build and model human behavior and cognition faithfully (Shneiderman 2020). This is in line with O'Neill et al. (2022) whose conceptualization of levels of automation and agency which recognizes that computer-based entities must meet a partial level of agent autonomy in order to recommend or execute actions spontaneously.

### 2.5. (2) Normative: What should AI be?

Oftentimes, the team member metaphor is critiqued drawing on a normative position (typically driven from philosophy, law, AI ethics) that centers on the responsibility, accountability, moral agency, and governance of AI systems (see e.g., Evans et al. 2025). A key question from this position is: What status can AI legitimately have? With the key implication being that AI must remain a tool to preserve human responsibility. The EU AI Act proclaims human oversight as a central safety mechanism for AI systems and states that "AI should be a tool for people" (European Commission 2021, p. 1). Thus, from this perspective, conceptualizing AI as a team member can be interpreted as a threat to two goals: to achieve human-centric AI systems (i.e., systems that are in line with and protect human needs, rights, and well-being), and human oversight of AI systems (i.e., it must be possible for humans to effectively oversee systems in operations; Enqvist 2023).

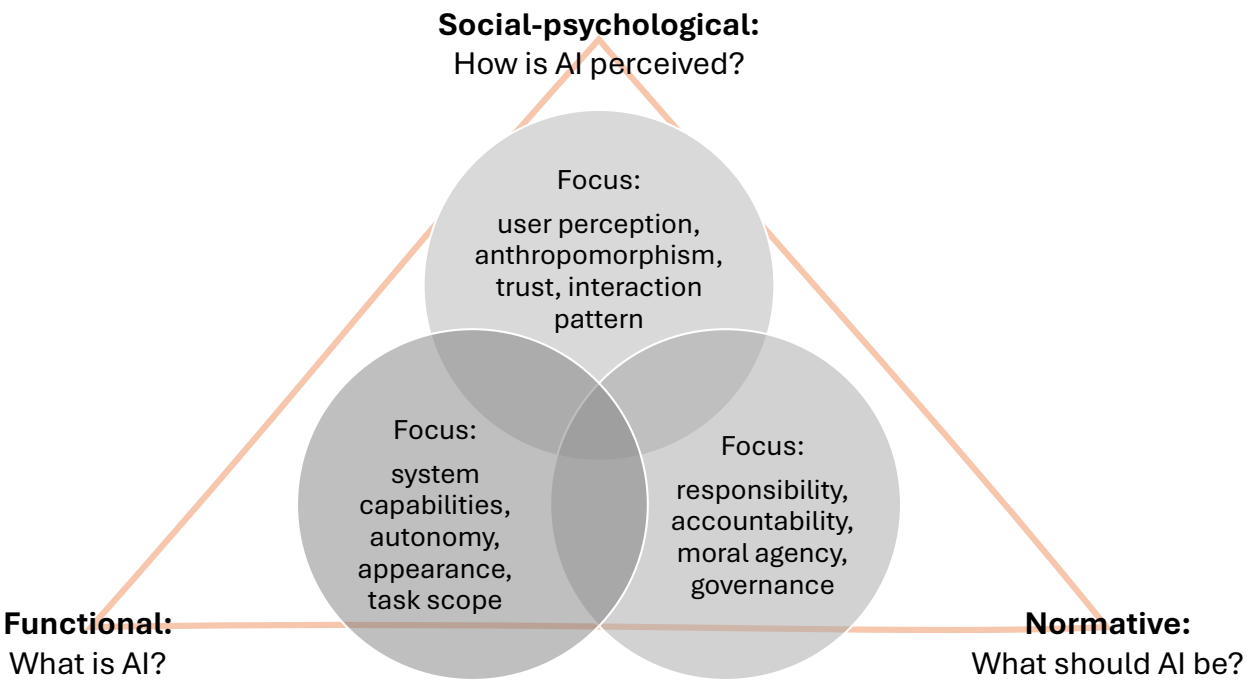



***Figure 1:*** *Three analytical angles shape the conceptualization of AI as a tool or team member.*

### 2.6. (3) Social-psychological: How is AI perceived?

The debate becomes less dichotomous when a third, social-psychological position is differentiated: from this perspective (usually driven from psychology, human-computer-interaction, human factors), user perceptions are at the center, with the key question being: how do people actually perceive and experience the interaction with an AI? Important research questions concern the perceived anthropomorphism, trust, and interaction patterns that emerge from people's experiences with AI. These factors shape individual perceptions of what AI is and what it does for and with users, regardless of whether AI is functionally designed or normatively understood as a tool or as a team member (e.g., Chen et al. 2024).

Thus, the tool perspective aligns strongly with the normative view and, depending on the context, might extend towards the social-psychological corner. The teaming conceptualization can be helpful from a functional perspective and is also driven from with the social-psychological corner. A conflict arises when a label from one corner is projected across all levels. For example, conceptualizing AI as a team member is normatively challenging, as it is in direct conflict with human-overview aspirations. However, people might still anthropomorphize a system - without assigning it moral membership in a team. Neither the tool nor the team member label is able to span the whole triangle.

Moreover, in suggesting these different analytical angles, we hope to make it evident that the problem is not the use of metaphors per se, but the unmarked projection of claims from one analytical level onto another. Functional descriptions are often taken to imply normative conclusions, while experiential accounts of human–AI interaction are sometimes treated as evidence for design or governance decisions without sufficient scrutiny. This slippage contributes to confusion in both research and practice, leading to design recommendations that are difficult to interpret, compare, or operationalize across workplace contexts.

## 3. INTERDEPENDENCIES BETWEEN ANALYTICAL PERSPECTIVES

Although we distinguish between functional, normative, and social-psychological perspectives analytically, these perspectives do not operate independently in practice. Instead, they are dynamically interrelated and influence one another in asymmetrical ways. We argue that many tensions surrounding human–AI collaboration emerge not only from conflating these perspectives, but also from misunderstandings about how developments on one analytical level propagate across the others.

Most importantly, changes in the functional properties of AI systems often shape social–psychological experiences and, indirectly, normative debates. As AI systems become increasingly autonomous, adaptive, proactive, and conversational, people are more likely to perceive and interact with them in relational and social terms.(Kim and Im 2023; Nass et al. 1996; Tschopp et al. 2023). For example, systems that communicate through natural language, maintain conversational memory, proactively provide recommendations, or coordinate tasks across workflows may evoke perceptions of intentionality, competence, or teammate-likeness even when they remain technically limited and organizationally governed as tools (Peter et al. 2025; Wynne and Lyons 2018). In this sense, social perceptions of AI are not arbitrary; they are partially enabled and constrained by system functionality and interaction design (Janson 2023; Rieth et al. 2026).

At the same time, social–psychological experiences may influence how AI systems are incorporated into organizational practices. Research on human–AI decision-making suggests that perceptions of AI competence, trustworthiness, and reliability shape how much users rely on algorithmic recommendations and how decision authority becomes distributed in practice (Puranam 2021; Lai et al. 2023). For example, if workers consistently experience AI systems as knowledgeable, collaborative, or trustworthy, they may become more likely to rely on AI recommendations, integrate AI outputs into routine work practices, and accord AI systems increasing influence over organizational decision-making. Empirical work supports this view, showing that AI systems perceived as more intelligent, agentic, or humanlike are more likely to be viewed as competent and trustworthy, increasing users' willingness to rely on their recommendations (Glikson and Woolley 2020; Kim and Im 2023; Waytz et al. 2014). Additionally, Mara et al. (2026) found that these perceptions are shaped by what people know about the systems.

Over time, such interaction patterns may affect how organizations structure coordination, supervision, and oversight around AI-supported work. Importantly, this does not imply that AI systems possess institutional membership, moral agency, or formal organizational authority. Rather, the claim is that social perceptions and interaction practices surrounding AI systems may become organizationally consequential by shaping how humans allocate attention, trust, responsibility, and decision-making authority in everyday work practices (Puranam 2021). From a practice-based perspective, the organizational effects of technology emerge not only from technical capabilities themselves, but also through recurrent patterns of interpretation and interaction surrounding their use (Orlikowski 2000). Hence, social–psychological and normative dynamics surrounding AI systems may partially emerge through the functional characteristics of these systems and the interaction practices they enable.

Likewise, normative perspectives can also dictate functionalities and social-psychological prescriptions. Rather than primarily describing what AI systems are or how they are experienced, normative perspectives prescribe what kinds of human–AI interactions are considered legitimate or desirable. Principles such as human oversight, accountability, transparency, or contestability therefore place constraints on how AI systems should be designed, integrated, and governed within work contexts (e.g., Jobin et al. 2019). From this perspective, normative commitments should shape functional system design, for example, by limiting autonomous decision-making authority or ensuring meaningful human control over critical decisions.

However, even while attempting to do so, normative positioning cannot fully determine the social experience of users. Even systems explicitly framed and governed as tools may still be perceived relationally by users. Anthropomorphic interface cues, conversational interaction modalities, or repeated workplace interactions may encourage users to develop trust, attachment, or perceptions of collaboration independent of organizational intent (Peter et al. 2025). In that regard, users' social-psychological understanding and interpretation build on perceived normative as well as technical cues - which can differ from actual system characteristics (see e.g., the Trustworthiness Assessment Model (TrAM) Schlicker et al. 2025). Consequently, tensions can emerge when normative framings, functional system properties, and social experiences become misaligned.

For example, organizations may normatively position AI systems as assistive tools while simultaneously implementing highly conversational and proactive interfaces that encourage teammate-like perceptions. Conversely, functionally autonomous systems may continue to be discussed as "mere tools" despite increasingly shaping decisions and workflows in ways that exceed traditional instrumental understandings of technology. Such mismatches can create practical and ethical challenges, including overtrust, diffusion of responsibility, unrealistic expectations, or uncertainty regarding accountability structures (see, e.g., Hannig et al. 2026).

Understanding these interdependencies draws attention to how functional capabilities, normative commitments, and social experiences co-evolve and occasionally conflict within organizational settings. The central challenge for future human–AI collaboration

research may therefore not be resolving the debate in favor of one metaphor, but understanding how these analytical perspectives interact and how tensions between them shape the design, governance, and lived experience of AI at work.

## 4. MOVING FORWARD

In this work, we contend that the debate between "AI as tool" and "AI as team member" persists largely because different analytical levels are being conflated. To that end, we want to stress that progress in research and practice requires more than introducing alternative terminology. It requires a change in how the research community articulates claims about AI systems and their role in work contexts. We therefore issue an explicit call to the human–computer interaction and work research communities to more carefully situate their claims and contributions within clearly defined analytical perspectives.

Concretely, researchers and designers should make explicit whether their arguments concern (1) functional properties of systems, (2) normative claims about responsibility, governance, and desirable futures of work, or (3) social–psychological phenomena concerning how people experience and interpret AI in practice. When presenting empirical findings or design recommendations, scholars should specify which of these perspectives their conclusions address and avoid projecting labels or assumptions from one analytical level onto another. For example, observing that workers treat an AI system as a teammate does not imply that the system should be granted social or moral standing, nor that it functionally operates as a teammate in organizational structures. Conversely, normative arguments insisting that AI must remain a tool do not negate the empirical reality that workers may experience collaboration with AI in relational terms. Making these distinctions explicit can help prevent conceptual slippage, reduce misunderstandings across disciplines, and improve the comparability and cumulative value of research findings.

In the end, reflecting on how discourse around AI evolves over time, we suspect that the worst that could come of this debate is silent acceptance of either of these terms. As Eriksson et al. (2025) point out, at some point, technology becomes so embedded in everyday work practices that it no longer receives explicit scholarly or public scrutiny, even as its social effects continue to unfold. The authors point to technologies such as the Internet of Things that have receded from visibility even as they reshaped infrastructures, normalized surveillance, and redistributed agency and control across social groups. We suspect that AI, as a tool or team, will be on a similar trajectory, rapidly becoming background infrastructure while conversations about its implications fade from view. The concern is not merely that AI will be taken for granted, but that the conceptual, ethical, and political choices encoded into these systems, including which values are privileged, who benefits from their integration, and who is marginalized by their pervasive use, will become harder to contest once the technology is no longer a topic of active debate. From our viewpoint, this reinforces the need for continuous critical engagement with how AI is conceptualized and discussed across analytical levels. If discourse collapses into platitudes or fades into the background, then ethical blind spots, power asymmetries, and unintended consequences may solidify into the very fabric of work and organizational life in ways that are difficult to reverse.

## 5. CONCLUSION

The goal of this article is to question a debate that has increasingly shaped how human–AI collaboration at work is studied, discussed, and designed: rather than asking whether AI should be understood as a team member or a tool, we have argued that this apparent opposition vanishes when accounting for three analytical levels: functional design of AI, social perceptions of AI, and normative commitments of what AI should be. By disentangling these levels, we have shown that seemingly contradictory positions can coexist: people may experience and interact with AI in team member-like ways, even as AI must remain a tool in normative and regulatory terms.

## 6. ACKNOWLEDGMENTS

We would like to thank the Center for Advanced Internet Studies (CAIS) for funding the workshop from which this work emerged.

The authors wish to acknowledge the use of ChatGPT 5.2 in the writing of this paper. This tool was used to assist with improving the language in the paper. The paper remains an accurate representation of the authors' underlying work and novel intellectual contribution.

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