

THE GENERATIVE AI DILEMMA IN KNOWLEDGE-INTENSIVE TEAMS

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Acknowledgments: The authors thank associate editor Dana Minbaeva and the three anonymous reviewers for their constructive feedback throughout the review process. We also wish to thank participants at the 2025 Academy of Management Annual Meeting in Copenhagen, Denmark for their developmental feedback on an earlier version of this work.

Author Accepted Manuscript

This is the author accepted manuscript of an article accepted for publication in *Academy of Management Review*. It has not been copyedited or typeset and may differ from the final published version of record, which is available at <https://doi.org/10.5465/amr.2024.0538>.

Please cite the published article: Reif, J. A., & Cummings, J. N. 2026. The generative AI dilemma in knowledge-intensive teams. *Academy of Management Review*. <https://doi.org/10.5465/amr.2024.0538>

THE GENERATIVE AI DILEMMA IN KNOWLEDGE-INTENSIVE TEAMS

ABSTRACT

In knowledge-intensive teams, collaborative interactions among teammates have historically served as the primary means through which members access task-relevant information, advice, and feedback. Generative artificial intelligence (AI), however, now offers members an alternative source of these resources. We develop a multilevel theory that proposes team members who are proficient with generative AI are more likely to perceive the resources it can offer as functionally equivalent to those they can access through their teammates. In turn, we propose that some members will shift their knowledge-seeking interactions to generative AI. As this substitution behavior accumulates within a team, the team's collaboration network is less likely to foster the critical emergent states that support team effectiveness. The key insight of our theory is a dilemma for knowledge-intensive teams: generative AI can boost team performance by helping members to work more efficiently, but a lack of collaboration among teammates can offset these gains and undermine team satisfaction.

The generative AI dilemma in knowledge-intensive teams

Teams are the dominant mode of organizing in knowledge-intensive settings (Bell et al., 2018; Cohen & Bailey, 1997). Theories of team effectiveness highlight the central role that member interaction processes play in shaping team outcomes (Hackman, 1987), and teams scholars have devoted considerable attention to understanding how members work together to accomplish their goals (Hoegl & Gemuenden, 2001; Woolley et al., 2008; Weingart et al., 2023). To examine these processes, researchers frequently adopt a network perspective wherein the density of ties that carry informational resources (e.g., information, advice, and feedback) is treated as a critical variable that shapes team effectiveness (Park et al., 2020; Balkundi & Harrison, 2006; Reagans & McEvily, 2003). Although prior literature acknowledges that teammates also access informational resources through technology, historically, resources from colleagues and technology have provided qualitatively different benefits (Haas & Hansen, 2007) and are rarely compared directly (cf. Lu & Yuan, 2011; Zimmer et al., 2007). For instance, while technology could quickly retrieve or manipulate electronically stored information (e.g., Sparrow et al., 2011; Knorr Cetina, 2010), it could not apply knowledge to new situations or engage in interactive problem-solving in the same way that a teammate could (Nebus, 2006; Shneiderman & Plaisant, 2010). Accordingly, the teams literature has emphasized ties among members as the primary conduits for informational resource flow within teams (e.g., Balkundi & Harrison, 2006; Chung & Jackson, 2013; Reagans & McEvily, 2003).

However, recent advancements in generative artificial intelligence (AI) challenge the distinction between the informational resources available through technology versus teammates. Through prompts written in natural language, members can turn to generative AI to seek informational resources that are tailored to their specific task needs, such as advice about how to

approach an unfamiliar problem (e.g., Osborne & Bailey, 2025) or personalized feedback on how to improve a work product (e.g., Hutt et al., 2024). While numerous experimental studies suggest generative AI enhances individual performance across a broad range of tasks commonly found in knowledge work settings (e.g., Boussioux et al., 2024; Jia et al., 2024; Noy & Zhang, 2023; Cui et al., 2024; Dell’Acqua et al., 2026), its ability to provide information, advice, and feedback that members may perceive as similar to that which they can access through collaborative interactions with teammates raises an important question in the context of team-based work: Does generative AI simply complement individual efforts, or does it substitute for collaborative interactions through which teammates share and integrate knowledge? If we extend prior work that assumes the informational resources from teammates and technology serve qualitatively distinct purposes (e.g., Haas & Hansen, 2007; Nebus, 2006), then members’ performance gains from generative AI should accrue directly to teams with minimal impact on teammate interactions. Conversely, if members perceive generative AI as an alternative pathway for accessing resources such as task-relevant information, advice, and feedback, critical interaction processes that support team effectiveness may suffer. The consequences of generative AI for team effectiveness thus hinge on the extent to which it functions as a complement to individual contributions or as a substitute for collaborative interactions among teammates.

The purpose of this article is to develop a theory of how generative AI shapes team effectiveness that accounts for both its potential to enhance individual productivity and to alter patterns of collaboration among teammates. Our central argument is that generative AI is uniquely capable of providing informational resources that members may perceive as similar to those available through teammates, which can lead members to shift their collaborative interactions away from teammates in ways that are consequential for team effectiveness. To

develop our model, we begin by defining key constructs – including knowledge-intensive teams, informational resources, and generative AI – and establishing the boundaries of our theory. We then argue that the features of generative AI will make it more likely that members who are proficient with the technology will perceive that it is capable of providing equivalent resources to those they can access through interactions with teammates. This perception, in turn, gives rise to substitution decisions that reduce the density of the team’s collaboration network. At the team-level, we propose that team-level generative AI proficiency and collaboration network sparsity have opposing effects on team performance, and that these relationships are moderated by features of the team’s task. We further argue that reduced collaboration among team members has negative implications for team satisfaction.

The key contribution of our theory to the teams literature is that we conceptualize the role of generative AI as not merely a complement to individual productivity, but as a substitute for the collaborative interactions among teammates that foster team effectiveness. A critical implication of this dual role of generative AI is a dilemma for knowledge-intensive teams: while generative AI can introduce valuable informational resources that enhance team performance, its negative impact on team collaboration may offset these performance gains and undermine team satisfaction. Figure 1 summarizes the core propositions of our theory.

[Insert Figure 1 about here]

KNOWLEDGE-INTENSIVE TEAMS, INFORMATIONAL RESOURCES, AND GENERATIVE AI: DEFINITIONS AND ASSUMPTIONS

Knowledge work – that is, work that “involves thinking as a core task, mental skills, a nonlinear work process, the derivation of new knowledge, and information as the primary work outcome” – is often carried out in teams (Devine, 2002: 296; Huang & Cummings, 2011; Chung & Jackson, 2013). A *knowledge-intensive team* is a set of individuals who work interdependently

to complete tasks requiring knowledge discovery or integration, such as new product launches, consulting engagements, or research projects (Hackman, 1987; Chung & Jackson, 2013; Brown & Eisenhardt, 1995; Anand et al., 2007; Ben-Menahem et al., 2016). These tasks tend to be complex and ambiguous, requiring team members to solve problems and learn as they carry out the work (Huang & Cummings, 2011). Although aspects of our theory may apply in other collaborative contexts (e.g., intra-organizational networks), knowledge-intensive teams are a theoretically important site for examining how generative AI reshapes collaborative processes because teams combine shared goals, joint accountability, and mutual interdependence that make collective outcomes particularly sensitive to changes in the quality and frequency of member interactions (Hackman, 1987; Wageman et al., 2012).

We expect the theory presented in this article to apply most directly to knowledge-intensive teams that meet three conditions. First, we assume that the interdependencies among members of the team are primarily knowledge-based, rather than based on rigid workflows or technical constraints (Raveendran et al., 2020; Chung & Jackson, 2013). In other words, a significant portion of the collaboration that occurs within the team involves the exchange of expertise among members. This flexibility is what enables teams performing structurally similar tasks to do so with varying degrees of interaction among members (Wageman & Gordon, 2005). Second, we assume that members have latitude to decide from whom or how they obtain at least some of the informational resources they use at work (Shea & Guzzo, 1987). Although this discretion may be more constrained in certain contexts (e.g., heavily regulated industries or hierarchical organizations), our theory assumes that members have at least some freedom to make choices about how they access informational resources. Finally, we assume that generative AI use is permitted in the team's organizational context.

We use the term *informational resources* to describe task-relevant, knowledge-based forms of assistance that inform the way members of the team execute aspects of the team's task. Team members seek informational resources from one another when they encounter situations (e.g., challenges or opportunities) in which they do not have the knowledge or confidence to proceed (Nebus, 2006). Unlike social resources such as emotional support and friendship (Lincoln & Miller, 1979; Ibarra, 1993), informational resources are sought to achieve task-related goals like solving problems or identifying opportunities (Nebus, 2006). For instance, members may approach one another for support with creative problem-solving (Shalley & Perry-Smith, 2008), such as to brainstorm the best way to complete a part of the task or to seek advice about how to resolve a technical issue. The exchange of informational resources among teammates supports team effectiveness by expanding the pool of knowledge available for the task and enabling the team to leverage its members' diverse expertise (Mesmer-Magnus & DeChurch, 2009; Cummings, 2004; Huang & Cummings, 2011; Bunderson, 2003). Although the exchange of informational resources is not the only form of collaboration in knowledge-intensive teams, prior work has highlighted that informational resource exchange is a "critical means by which interdependent team members achieve performance synergies in knowledge-based teams" (Farh et al., 2017: 1120). Our theory focuses on three specific informational resources – information, advice, and feedback – that have each received significant attention in the teams literature (e.g., Park et al., 2020; Mesmer-Magnus & DeChurch, 2009; Haas & Hansen, 2007; Ashford & Cummings, 1983; Seers et al., 1995) and broader interpersonal resource seeking literature (see Lim et al., 2020 for a review).

Finally, AI refers to systems that perform "cognitive functions that are associated with human minds" (Raisch & Krakowski, 2021: 192). *Generative AI* is a class of AI-based

technologies that can produce new content based on prompts written in natural language (Mollick, 2024). In this article, we use the term generative AI to refer to general purpose AI-enabled assistants that augment or automate aspects of a human team member's work rather than act as an independent agent with complementary goals (Raisch & Krakowski, 2021; cf. Harris-Watson & Larson, 2026; O'Neill et al., 2022). Examples of such assistants include ChatGPT by OpenAI, Claude by Anthropic, and Gemini by Google. We focus our theory on generative AI assistants because it is the most pervasive form of AI in knowledge-intensive settings (McKinsey & Company, 2025) and can be utilized for a broad range of tasks (Alavi et al., 2024). Our theory is agnostic to whether the generative AI system is trained on exclusively public data or incorporates proprietary firm data (Valentine et al., 2025), but we discuss how training data may influence the strength of the proposed relationships in Future Research Directions.

Although generative AI is a rapidly evolving technology, our theory focuses on two defining features that distinguish it from traditional tools¹: (1) its capacity to adapt and (2) its ability to interact through natural language. In the next section, we will argue that these two unique features increase the likelihood that team members who are proficient with generative AI will perceive that it can provide information, advice, and feedback that are functionally equivalent to what they can access through interactions with teammates.

GENERATIVE AI AND INFORMATIONAL RESOURCE EXCHANGE IN TEAMS

Knowledge-intensive tasks tend to be characterized by equifinality – a property of complex systems in which multiple pathways exist for attaining the same end state (von Bertalanffy, 1968; Katz & Kahn, 1978; Gresov & Drazin, 1997; Chung & Jackson, 2013). Because there is rarely a single 'right' approach to completing a knowledge-intensive task

¹ We use the term *traditional tools* to refer to technologies that operate based on fixed, preprogrammed rules (Chalmers et al., 2021).

(Wageman & Gordon, 2005), members may perceive that they have multiple paths to access the informational resources they require to achieve their goals (Kruglanski et al., 2002). This configuration invites choice on the part of the member because there are multiple pathways to fulfill a requirement (Child, 1972; Kruglanski et al., 2002; Merton, 1967). Resources are *functionally equivalent* if they fulfill the same basic function or purpose (Gresov & Drazin, 1997; Merton, 1967; Halbesleben et al., 2014). For instance, a member who requires guidance on how to approach a task may have multiple teammates from whom she could seek advice (Nebus, 2006). Similarly, either a physical dictionary or an online dictionary can provide a word's definition. Functional equivalence does not imply that two resources are literally the same, nor that accessing them incurs equal costs and benefits. Functionally equivalent resources may differ in their quality and accessibility (Zimmer et al., 2007), such that one offers a more desirable path for achieving a goal than another (e.g., a quick online search versus a trip to the library across town). However, when members perceive that two or more resources are functionally equivalent as a means to help them achieve their goals, they may consider the costs and benefits associated with each (Gresov & Drazin, 1997; Huang & Zhang, 2013; Kruglanski et al., 2011).

Historically, interpersonal relationships among team members have served as the primary conduits through which informational resources flow within teams (Balkundi & Harrison, 2006). For this reason, teams are often studied from a network perspective wherein each team member is a 'node' and the connections between members form 'ties' that link to create the team's network structure (see Park et al., 2020 for a review). These ties function as the 'pipes' through which informational resources flow (Podolny, 2001), and stronger ties represent more frequent resource flows (Granovetter, 1973; Park et al., 2020). Although numerous traditional tools also provide informational resources (e.g., Sparrow et al., 2011; Davenport & Prusak, 1998), prior

scholarship has highlighted that informational resources available through technology typically complement rather than substitute for those available through teammates (Haas & Hansen, 2007; Leonardi & Treem, 2012; Cross & Sproull, 2004). In particular, informational resources available through teammates were qualitatively distinct from those accessible through technology because teammates could apply their knowledge to novel contexts and problems, rather than retrieving static information or applying fixed rules, and engage in interactive dialogue that allowed the requester to clarify needs and refine the resource to their specific situation (Nebus, 2006; Cross & Sproull, 2004). We suggest that the two unique features of generative AI – its capacity to adapt and to interact in natural language – increase the likelihood that members perceive they can access functionally equivalent informational resources from generative AI or teammates.

First, generative AI is unique relative to traditional tools in its ability to adapt to perform a range of tasks, learn, and act on feedback. Research on technology in organizations has conceptualized computer-based tools as having fixed features that limit the operations users can perform (Griffith, 1999; DeSanctis & Poole, 1994). Existing theoretical frameworks cast workplace tools as a mechanisms for accomplishing aspects of cognitive work that can be codified into a set of explicit rules (Autor et al., 2003; Parker et al., 2017; Hui et al., 2024), while positioning colleague interactions as useful for cognitive work that requires flexible thinking, such as complex problem-solving and creative idea generation (Byron et al., 2023; Cross et al., 2001; Burt, 2004). However, unlike tools that “rely on a fixed set of preprogrammed instructions” (Chalmers et al., 2021: 1030), generative AI can mimic human reasoning across diverse cognitive domains and learn from examples (Vanneste & Puranam, 2024; Brynjolfsson et al., 2025). Generative AI is thus flexible in that it can adapt to perform a variety of different

tasks and change the way it performs those tasks based on new information or instructions. This capacity to perform wide-ranging actions that extend beyond an explicit set of rules enables generative AI to support users across a range of tasks commonly found in knowledge work settings (Iorliam & Ingio, 2024; Anthony et al., 2023; Murray et al., 2021).

Second, generative AI differs from traditional tools in its capacity to interact in natural language (Boussieux et al., 2024). Traditional tools enable users to access a particular set of information and perform specific operations through features such as navigation menus and search bars (e.g., Shneiderman & Plaisant, 2010; Colbert et al., 2016; Cross & Sproull, 2004; Haas & Hansen, 2007), whereas colleagues “provide immediate and focused responses given specific questions” (Lu & Yuan, 2011: 136). By contrast, generative AI uses natural language dialogue as its primary mode of interaction (Boussieux et al., 2024). Team members interacting with generative AI can provide dynamic instructions, request clarifications, and probe AI output through an interactive process (e.g., “Help me make this pitch more concise” or “Revise your response considering the customer’s perspective”). This feature enables generative AI to continuously improve the informational resources it provides based on two-way conversations with the user.

Although generative AI’s capacity to adapt and interact in natural language builds on decades of innovation in machine learning, natural language processing, and human-computer interaction (Vaswani et al., 2018; Bommasani et al., 2021; Fui-Hoon Nah, 2023), we suggest the combination of these features enables it to provide information, advice, and feedback that more closely resembles that historically provided by a teammate than a traditional tool could. Thus, members who are skilled in utilizing these features can access informational resources that they may perceive as serving the same purpose as those they would otherwise obtain from teammates.

In the following paragraphs, we describe how these features enable generative AI to provide each type of informational resource in ways that differ from traditional tools. Table 1 summarizes these comparisons.

[Insert Table 1 about here]

Information. Members of knowledge-intensive teams depend on both tools and teammates for task-relevant information (Haas & Hansen, 2007; Mesmer-Magnus & DeChurch, 2009). Traditional tools allow teammates to access vast amounts of information from public sources (e.g., the Internet) and internal systems (e.g., intranets). Although these traditional tools efficiently surface the information to which they have access (Davenport & Prusak, 1998; Hansen & Haas, 2001; Cross & Sproull, 2004), their functions are limited to filtering and retrieval. For information that is tailored to specific needs, team members instead turn to teammates who can apply their knowledge to a particular question or task (Haas & Hansen, 2007; Argote et al., 2021; Nebus, 2006). However, generative AI can synthesize information, apply it to new situations, and refine it through interactions with the requester. This level of customization was not possible with traditional tools that lacked the ability to adapt based on new instructions or provide an interpretation of the data they retrieved (Alavi et al., 2024). Thus, the information obtained through interactions with generative AI more closely mirrors the level of task-specific customization of information accessed through teammates than traditional tools.

Advice. When confronting a task-related challenge, team members often turn to one another for advice (Zhang & Peterson, 2011; Hollenbeck et al., 2015). Given that advice is typically sought in novel situations (Bonaccio & Dalal, 2006) that require creative problem-solving (Brennecke, 2020), traditional tools that operate based on pre-programmed rules are limited in their ability to provide it. Tools such as decision support systems overcome this

limitation by providing recommendations for recurrent decisions for which there is a finite set of alternative options (Nunes & Jannach, 2017), but these tools cannot adapt to reason through complex, open-ended problems. Accordingly, team members turn to one another for advice about situations that require more nuanced evaluations, such as suggestions for how to solve a problem or approach a task (Cross et al., 2001). However, generative AI's ability to adapt and interact in natural language enables it to engage in open-ended reasoning, to respond to contextual cues from the member, to evaluate trade-offs, and to explain its recommendations (Rebholz et al., 2024; Osborne & Bailey, 2025). These capabilities enable it to provide task-relevant advice that is more akin to that from teammates than traditional tools.

Feedback. Finally, team members rely on one another for feedback – evaluative information about current performance (Marks et al., 2001; Sherf & Morrison, 2020). For example, team members may provide input on ideas or identify errors (Poltrock et al., 2003; Edmondson et al., 2004). Providing feedback requires an evaluator to critically examine a target (e.g., behavior or work product) and determine whether it achieves a particular goal (Ashford, 1986). Traditional tools are limited in their ability to meet these criteria, except in narrow domains with well-defined rules. For instance, tools such as spellcheckers and code debuggers can identify syntax errors but cannot offer nuanced evaluations of writing or code quality. By contrast, generative AI can evaluate targets against an adaptable set of standards that it learns from examples. This enables it to provide more nuanced feedback, such as assessing the flow of a presentation or spotting a logical gap in an argument. Members who do not understand its feedback or who disagree with its standards can prompt generative AI to seek more specific guidance or reorient its evaluation criteria. These exchanges more closely resemble the two-way

feedback interactions that occur among teammates than the limited feedback available through traditional tools.

Generative AI Proficiency and Perceived Teammate-AI Functional Equivalence

We have argued that two unique features of generative AI – its ability to adapt and to interact in natural language dialogue – enable it to provide informational resources that more closely resemble those available through teammates than traditional tools could provide. Extending the concept of equifinality to an evaluation of the resources available through teammates and generative AI, we define perceived *teammate-AI functional equivalence* as the extent to which members consider generative AI as functionally capable of providing the same informational resource that a teammate can provide. Perceived teammate-AI functional equivalence reflects a belief that informational resources available through generative AI can fulfill the same goals as those available through interactions with teammates. It is not a personal preference, but rather a goal-oriented evaluation of whether a particular requirement (e.g., feedback on a work product or advice about how to approach a task) can be fulfilled either by generative AI or a teammate. Practically, perceived teammate-AI functional equivalence could be measured by adapting an existing perceived substitutability scale (e.g., Lamberton & Rose, 2012; Flavián & Gurrea, 2007) such that team members evaluate the extent to which informational resources accessible through generative AI substitute for those available through teammates and vice versa.

Whether members perceive resources available through their teammates and generative AI as functionally equivalent should depend on how skilled they are in utilizing its differentiating features. Employees who have access to the same technologies can vary widely in their proficiency in operating them (Evans & Simkin, 1989; Santhanam & Sein, 1994; Mullins &

Cronan, 2021; Yi & Davis, 2003). When new technologies arrive in the workplace, some employees seek to master them while others avoid using them at all (Barley, 1990). Even among members who use a tool, some may “black box” it while others attempt to understand all of its features and potential capabilities (Anthony, 2018; 2021). Like with past workplace technologies, we expect there will be member-level differences in generative AI proficiency within teams.

Generative AI proficiency is the extent to which individuals can effectively produce purposeful outputs using generative AI systems. This construct reflects the skills that enable individuals to take advantage of generative AI’s adaptability and capacity to interact in natural dialogue (e.g., recognizing the range of tasks that generative AI can support and crafting clear, effective prompts, Mollick, 2024), as well as an understanding of how generative AI technologies work (Long & Magerko, 2020). For example, more proficient members may leverage generative AI’s adaptability by providing examples from which it can learn task-specific patterns or by instructing it to adopt particular perspectives (Mollick, 2024). Similarly, they may engage in in multi-turn dialogues that progressively clarify assumptions or requirements, such that the output that generative AI supplies is tailored to the members’ needs (Boussiou et al., 2024). Members with lower proficiency, however, may use generative AI like traditional tools, issuing simple retrieval or summary requests that do not leverage its adaptive or interactive capabilities. Generative AI proficiency is distinct from general competence in one’s domain of work (Krakowski, Luger, & Raisch, 2023), and may stem from differences in training (Kim, Chung, & Yu, 2013), experience (Bennett, Maton, & Kervin, 2008), and beliefs about the technology (Venkatesh, Morris, Davis, & Davis, 2003).

Members who are more proficient with generative AI may develop stronger expectations that it can reliably provide informational resources that help them achieve their goals (Vroom, 1964; Van Eerde & Thierriy, 1996). These positive expectations encourage more frequent use of generative AI and more ambitious use cases (Marcolin et al., 2000). As members experience successful outcomes from using generative AI to access informational resources, they may strengthen their view that generative AI is a viable alternative to seeking information, advice, or feedback from teammates. This strengthened expectation of generative AI's utility in achieving their objectives should increase perceptions of teammate-AI functional equivalence.

Alternatively, members who are not proficient may be less successful in accessing customized, informational resources from generative AI that support them in achieving their goals at work. Members who are lower in generative AI proficiency should thus be less likely to view informational resources available from generative AI versus teammates as functionally equivalent.

For example, consider how different levels of generative AI proficiency might shape perceptions among members of a consulting team conducting a market analysis. A member who is not proficient with generative AI may use it for a basic research task, such as summarizing the demographics of a particular market. Although the information it retrieves is useful for the task, it represents a resource the member might have otherwise accessed through a traditional tool (i.e., a web search) rather than a teammate. This interaction with generative AI preserves rather than reduces the perceived distinction between informational resources available from generative AI versus teammates. Conversely, a member who is highly proficient with generative AI may prompt it with examples of market analyses conducted for other clients and ask it to critique her own portion of the analysis based on the standards it learns from these examples. In return, she

receives detailed and personalized feedback that much more closely resembles that which she might have obtained from a teammate than that available through a traditional tool. These different modes of engaging with generative AI based on proficiency are likely to generate different expectations of whether generative AI can provide functionally equivalent resources to teammates, as members should be especially likely to perceive functional equivalence when their method of interacting with it takes advantage of generative AI's unique ability to adapt and to interact in natural language.

In summary, we propose:

Proposition 1: *Team members who are more proficient with generative AI are more likely to perceive informational resources available through generative AI and teammates as functionally equivalent.*

Perceived Teammate-AI Functional Equivalence and Collaboration Network Sparsity

Thus far, we have argued that members who are more proficient with generative AI are more likely to perceive that it can offer information, advice, and feedback that is functionally equivalent to that which they can access through interactions with teammates. Building on this foundation, we propose that members with high levels of perceived teammate-AI functional equivalence will, at least sometimes, choose to seek informational resources from generative AI instead of their teammates. This shift should reduce the extent to which team members work together to complete the team's task, thus decreasing the density of the team's collaboration network. We use the broad term *collaboration* to refer to the process of members working together to achieve some aspect of the team's task (Katz & Martin, 1997; Wageman et al., 2012). Examples of activities that constitute collaboration include exchanging knowledge pertinent to the task (Cross & Sproull, 2004), generating ideas together (Kavadias & Sommer, 2009), and collectively solving task-relevant problems (Kerrissey et al., 2021). Although team members

may collaborate for other purposes (e.g., to set goals or monitor team progress, Marks et al., 2001), informational resource exchange is a critical aspect of collaboration in knowledge-intensive settings (Farh et al., 2017; Nebus, 2006; Wageman et al., 2012; Huang & Cummings, 2011).

Because the team-level collaboration network structure emerges from members' interaction choices, we now consider how member-level perceptions of teammate-AI functional equivalence shape the team's collaboration network density. Teams research that adopts a network perspective has highlighted that the intensity of collaboration among different pairs of members within the team can vary (Crawford & LePine, 2013; Chung & Jackson, 2013; Schulte et al., 2012). *Collaboration network density* (or its inverse, *sparsity*) refers to the average strength of collaboration ties between each pair of members on the team (Park et al., 2020; Sparrowe et al., 2001; Tröster et al., 2014).

A key reason that team members initiate collaborative interactions with teammates is that they encounter “a problem or opportunity the individual does not have sufficient confidence or knowledge to solve alone” (Nebus, 2006: 617). In such moments, the member perceives that information, advice, or feedback would help reduce uncertainty or guide next steps, and that someone else on the team can provide it (Lim et al., 2020; Nebus, 2006). These task-related exchanges create opportunities for reciprocal knowledge sharing (Myers, 2021) and help members develop familiarity with one another's expertise (Maloney et al., 2019). Further, such interactions lay the foundation for future collaboration by building familiarity, trust, and reciprocity, which reinforce patterns of working together (Dahlander & McFarland, 2013; Maloney et al., 2019).

We propose that team members who perceive teammate-AI functional equivalence face recurring choices about whether to seek informational resources through collaborative interactions with their teammates or from generative AI. Theories of social exchange posit that actors consider benefits and costs when choosing how to access resources (Blau, 1964; Homans, 1958; Cropanzano & Mitchell, 2005). Although not every collaboration choice may be informed by a precise analysis, we suggest that members who perceive informational resources available from teammates and generative AI as functionally equivalent will attend to the relative costs and benefits of each source. This comparison should often favor generative AI because it requires no coordination (Borgatti & Cross, 2003; Malone & Crowston, 1994), avoids the social costs of revealing knowledge gaps to teammates (Goffman, 1959; Goldsmith & Fitch, 1997; Thompson & Bolino, 2018), and does not create reciprocal obligations to provide resources to others in the future (De Jong et al., 2017; Hergueux et al., 2023). Although members may sometimes perceive teammates as offering higher-quality resources or simply prefer working with teammates, the lower time and social costs of consulting generative AI suggest that substitution will occur for some collaborative interactions. Critically, these substitution decisions are guided by members' immediate task-related needs and do not necessarily consider the broader team-level consequences of reduced collaboration, which are diffuse, delayed, and difficult to attribute to any single interaction.

As members who perceive functional equivalence increasingly turn to generative AI to fulfill their informational resource needs, the collaboration ties among pairs of teammates should weaken. This occurs because informational resource exchanges constitute a primary driver of collaboration tie formation and maintenance in knowledge-intensive settings (Nebus, 2006; Cross & Sproull, 2004; Huang & Cummings, 2011). Although it is possible that members who

start turning to generative AI for informational resources may begin collaborating with teammates in different ways (e.g., a member who previously contacted a teammate for technical advice she can access through generative AI may instead turn to that teammate for brainstorming), such shifts are unlikely to fully offset the reduction in collaboration because informational resource seeking tends to occur in response to specific task demands that emerge in the work process (e.g., Nebus 2006; Lim et al., 2020). Moreover, as collaboration ties weaken from reduced use, members become less aware of when and how to collaborate with specific teammates on other aspects of the task, further limiting future collaboration. Without the regular informational exchanges that previously sustained these relationships, collaboration network density should decline.

Although we argue that perceived teammate-AI functional equivalence drives members' initial decisions to seek informational resources from generative AI instead of teammates, it is important to note that this behavior may have cascading effects within the team (Mathieu et al., 2014). Resource exchange in teams tends to operate through implicit norms of reciprocity, such that members maintain balance in their relationships by helping those who have supported them and vice versa (Hergueux et al., 2023; De Jong et al., 2017). When members initiate fewer collaborative interactions with their teammates because they are turning to generative AI instead, other members may take notice and adapt their own behavior in response. This interactive withdrawal may further amplify collaboration network sparsity within the team.

For an illustration of how this substitution process influences team-level collaboration network structures, consider the three teams depicted in Figure 2. In Team A, all members perceive low teammate-AI functional equivalence, and thus members regularly contact one

another for information, advice, and feedback. These regular exchanges strengthen the collaboration ties among them, and thus the team's collaboration network is relatively dense.

[Insert Figure 2 about here]

On Team B, however, several team members have strong perceptions of teammate-AI functional equivalence while others do not. Members who perceive teammate-AI functional equivalence begin to shift their information seeking away from teammates and towards generative AI, while others continue to engage their colleagues more regularly. Some collaboration ties among members thus remain strong while others weaken due to one or both members shifting collaborative activity to generative AI. The resulting collaboration network structure is a mix of stronger and weaker collaboration ties among members, or a moderately dense collaboration network.

Finally, on Team C, all members of the team perceive high teammate-AI functional equivalence and thus typically turn to generative AI rather than teammates when they require informational resources. This behavior becomes the norm within the team. Consequently, members have fewer task-related interactions with one another, resulting in weaker collaboration ties among them. The collaboration network structure on this team is thus more sparse (less dense) than on Teams A and B.

In summary, we propose:

Proposition 2: *All else equal, team members with higher levels of perceived teammate-AI functional equivalence will more frequently replace informational resource seeking from teammates with informational resource seeking from generative AI, increasing the sparsity (decreasing the density) of the team-level collaboration network.*

IMPLICATIONS OF GENERATIVE AI FOR TEAM EFFECTIVENESS

We opened this article by proposing that generative AI has competing implications for team performance and can undermine team satisfaction. We now turn our attention to these

outcomes. Hackman's (1987) seminal model proposes that *team performance* and *team satisfaction* are key dimensions of team effectiveness (see also Sundstrom, De Meuse, & Futrell, 1990). *Team performance* refers to whether the team achieved its goals and is often measured through objective criteria that are specific to the team's task (e.g., profitability, approved patents, client satisfaction) or subjective measures such as executive ratings (e.g., Bunderson & Sutcliffe, 2002; Choudhury & Haas, 2018; Joshi et al., 2006; Kirkman & Rosen, 1999). *Team satisfaction* is the extent to which the team provides a rewarding experience to its members (Hackman, 1987). Team satisfaction focuses strictly on members' affective response to the team and does not imply successful performance (Bell & Marentette, 2011). Measures of team satisfaction include items such as, "I am very satisfied with working in this team" (Gladstein, 1984). We theorize that generative AI has implications for both team performance and satisfaction.

Team Performance

Members of knowledge-intensive teams are typically responsible for a portion of the team's task and must coordinate their work for collective task performance (Hackman, 1987; Steiner, 1972; Wageman, 1995; Marks et al., 2001). Team success depends on members' independent contributions and how well the team manages task and knowledge interdependencies (Raveendran et al., 2020; Mark et al., 2005; Mathieu et al., 2014). Given that both individual contributions and member interactions shape team performance, we suggest that generative AI will have competing implications for performance: Members who are proficient with generative AI will achieve productivity gains due to the efficiency with which they can access informational resources that complement their independent work, but the collaboration network sparsity that results from members shifting task-related interactions to generative AI will undermine team cognition, offsetting some of these performance gains.

Team-level *generative AI proficiency* refers to the collective extent to which team members are proficient in working with generative AI. It is a compositional construct operationalized as the average of team members' generative AI proficiency levels (Klein & Kozlowski, 2000).² The customized informational resources that members who are more proficient with generative AI can access on demand as they complete their work should support them in completing it effectively. This is consistent with numerous studies demonstrating that generative AI can enhance individual performance on tasks, such as idea generation, problem-solving, writing, and coding (Boussiou et al., 2024; Noy & Zhang, 2023; Jia et al., 2024; Barke et al., 2023).

Although some resources members access through generative AI may substitute for those teammates typically provide, in many cases they may be *incremental* rather than substitutive. As discussed previously, members of knowledge-intensive teams access informational resources through a combination of traditional tools and teammates. Informational resource exchange among teammates can improve performance (e.g., Mesmer-Magnus & DeChurch, 2009), but also incurs time and social costs (Leroy, 2009; Goffman, 1959). Continuously seeking information, advice, and feedback from teammates is thus not practical due to the attentional and social resources it would deplete, so members may not always seek these resources even when they would find them valuable for achieving their goals. Because generative AI lacks teammates' time and attentional constraints, members are likely to seek informational resources from it that they would not have otherwise sought from teammates. These informational resources are therefore incremental, expanding the pool of informational resources available to the team. We expect an increase in informational resource availability to positively affect team performance.

² Alternative operationalizations of generative AI proficiency, such as the percentage of the team that is proficient with generative AI, would yield similar predictions.

For example, if members of an analytics team are proficient with generative AI, they may continuously seek information, advice, and feedback from generative AI throughout the workday. As a result, they can prepare high-quality analyses more quickly than they otherwise could, because any time they get ‘stuck’ or have a technical question, generative AI is available on-demand to assist. However, this support does not replace collaborative interactions with teammates, as members constantly approaching teammates for assistance would be highly disruptive (Birnholtz et al., 2007) and may signal a lack of competence (Goldsmith & Fitch, 1997). This support, therefore, represents an expansion of the resources otherwise available to the team.

In summary, when members of the team are more proficient in using generative AI to perform their tasks, the team should experience improved performance because they can produce high-quality work more efficiently. We therefore propose:

Proposition 3: *Team-level AI proficiency is positively associated with team performance due to increased access to informational resources available through generative AI.*

Although teams may experience performance gains when their members are more proficient with generative AI, we have also argued that collaboration ties among members will weaken as a result of members shifting their informational resource seeking behavior to generative AI. A key question is thus how the collaboration network sparsity that results from members shifting their interactions to generative AI will influence team performance.

On the one hand, one could reasonably argue that the shift to teammates collaborating less with one another and more with generative AI could improve the overall efficiency with which the team completes its work. Collaboration among teammates imposes coordination costs (Malone & Crowston, 1994), which can distract from work and reduce the time members have available to work on the task (Leroy, 2009; Chung & Jackson, 2013). If many of the benefits of

collaboration are now available through generative AI (Anthony et al., 2023), it is plausible that intrateam collaboration is less critical for team performance than has historically been the case. From this efficiency-oriented lens, generative AI could improve team performance by reducing coordination burdens while still providing access to many informational resources that are superior to those available through traditional tools (Alavi et al., 2024).

On the other hand, performance in knowledge-intensive teams depends on how well members combine their collective expertise to develop new knowledge and apply it to a complex, ambiguous task (Hoegl & Gemuenden, 2001; Bunderson, 2003; Huang & Cummings, 2011). While efficiency helps teams meet budgets and schedules, it rarely drives performance for nonroutine tasks that require producing or synthesizing knowledge (Faraj & Sproull, 2000; Chung & Jackson, 2013). Instead, successful performance requires the team to develop and maintain a shared understanding of the task, which is likely to evolve as it is completed, and to integrate their contributions into a coherent solution (Wageman & Gordon, 2005; Huang & Cummings, 2011). For this reason, *team cognition* – a team emergent state that characterizes “how knowledge is mentally organized, represented, and/or distributed among team members” (Niler et al., 2021: 145) – is widely considered crucial for team performance in knowledge-intensive work (Grand et al., 2016; DeChurch & Mesmer-Magnus, 2010). We argue that collaboration network sparsity undermines this critical emergent state and, consequently, reduces performance in knowledge-intensive teams.

Teams scholars distinguish between processes and emergent states as separate but mutually reinforcing inputs to team outcomes (Marks et al., 2001). Team processes – such as collaboration – involve members interacting with one another in service of a task-focused outcome (Crawford & LePine, 2013). Emergent states refer to properties of the team that vary as

a function of team processes and other aspects of the task environment (Marks et al., 2001).

Unlike processes, which are behavioral in nature, emergent states represent dynamic “products of team experiences (including team processes) and become new inputs to subsequent processes” (Marks et al., 2001: 358).

Team cognition encompasses shared understanding of the team’s task, goals, and roles (team mental models, Cannon-Bowers et al., 1993) and accurate understanding of who knows what (transactive memory, Lewis, 2004) (Niler et al., 2021). These two components of team cognition work in concert to support team performance (DeChurch & Mesmer-Magnus, 2010). Team mental models provide members with a common framework for interpreting task demands and expectations, allowing them to anticipate what actions will be required and how their work fits within the broader team effort (Mohammed & Dumville, 2001; Kozlowski & Ilgen, 2006). In contrast, transactive memory provides members with a cognitive map of the team’s distributed expertise, enabling members to locate and access specialized knowledge efficiently (Wegner, 1987; Moreland, 1999). Together, these facets of team cognition support team performance by enabling members to coordinate their actions (Kozlowski & Ilgen, 2006), divide labor effectively based on expertise (Lewis, 2004), and utilize their collective knowledge to solve problems (Argote, 2024).

We propose that the collaboration network sparsity that results from members shifting their informational resource seeking behavior to generative AI will undermine team cognition, thereby reducing team performance. Dense collaboration networks facilitate team cognition because frequent interactions help members align their understanding of the team’s task (Mohammed & Dumville, 2001; Crawford & LePine, 2013) and learn about one another’s expertise (Moreland & Myaskovsky, 2000). For example, as members collaborate, their

interactions may surface differences in how members interpret task goals (Cronin & Weingart, 2007). Similarly, collaborative interactions allow members to observe one another's expertise in action (Lewis, 2004) and clarify who holds knowledge that is critical for successful task performance (Huang & Cummings, 2011). The strong team cognition that develops through these interactions facilitates team performance by minimizing coordination failures and ensuring that relevant knowledge is brought to bear in service of the task (Malone & Crowston, 1994; Argote & Fahrenkopf, 2016; Stasser & Titus, 1985; Uzzi & Lancaster, 2003). Conversely, when collaboration among members is less frequent because they turn to generative AI for informational resources, teammates have fewer opportunities to align their understanding of the team's task and update their collective understanding of who knows what. As a result of weaker team cognition, the team is more likely to experience difficulties coordinating work and utilizing members' distributed knowledge (Heath & Staudenmayer, 2000; Mohammed et al., 2021). These challenges reduce the team's ability to perform its task successfully.

Although decreased collaboration network density from members seeking informational resources from generative AI should precede weakened team cognition, this relationship is bidirectional. Processes and emergent states mutually influence one another through feedback loops (Marks et al., 2001), and thus the interplay we suggest between collaboration network sparsity and team cognition is likely to be dynamic and self-reinforcing over time. For example, teams that collaborate less frequently are less likely to develop shared knowledge of one another's expertise. This reduced awareness of what each member knows then makes it more difficult to identify future situations that would benefit from collaboration. This suggests a negative spiral in which sparse collaboration networks prevent the development of team cognition, which then reduces members' ability to collaborate effectively in the future. Such a

cycle should lead to even sparser collaboration networks over time, further constraining team performance.

As a demonstration, consider how the performance of a marketing team working on a new product launch might be affected by a sparse collaboration network. If members of the team collaborate infrequently because they primarily seek informational resources from generative AI rather than one another, they may fail to develop a shared understanding of the product's target customer and positioning strategy. For instance, while developing launch materials, one member might be focused on emphasizing the product's technical innovation while another is focused on its ease of use for non-technical buyers. These differing interpretations of the positioning strategy would surface quickly if the members regularly work collaboratively, yet may not be discovered until later if they primarily work independently with generative AI. Further, because they are less likely to be aware of what one another are working on, they are less likely to recognize situations in which they would benefit from consulting one another. Consequently, they execute their parallel workstreams in a way that makes them more difficult to integrate into a coherent go-to-market plan later.

In summary, we expect that the sparse collaboration networks that result from members shifting their informational resource seeking interactions to generative AI will weaken team cognition, reducing the team's ability to execute its task effectively. This performance loss may offset some or all of the performance gains that generative AI proficiency offers to the team.

Proposition 4: *Collaboration network sparsity is negatively associated with team performance due to weakened team cognition.*

Task-based Contingencies of the Relationships between Generative AI Proficiency, Collaboration Network Sparsity, and Performance

Thus far, we have proposed that generative AI leads to competing implications for team performance through two distinct mechanisms. Team-level generative AI proficiency enhances performance by expanding members' access to informational resources that support their contributions to the team's task, while the team collaboration network sparsity that results from members shifting their interactions to generative AI can undermine performance by weakening team cognition. Yet, the importance of these two mechanisms for team performance may vary depending on characteristics of the team's task.

Teams scholarship has long recognized that task characteristics shape which team composition variables and intrateam processes are most critical for performance (McGrath, 1984; Hackman, 1987). For instance, when teams perform structured additive tasks (i.e., tasks for which the sum of each member's individual contribution constitutes team performance), the group members' average ability levels are more strongly associated with team performance, and team processes are less central to team performance (Bell, 2007). However, for tasks that are less structured (e.g., uncertain, complex, or ambiguous), members' existing knowledge is less likely to be useful for task performance and effective team processes – which facilitate learning – are more strongly associated with team performance (Devine & Kozlowski, 1995; Wood, 1986). Given that knowledge-intensive teams perform a variety of different tasks and that the variables that influence team performance are dependent on the nature of the team's task (Bell 2007; Curral et al., 2001), the strength of the relationships between team-level generative AI proficiency and team performance as well as collaboration network sparsity and team performance should be contingent on characteristics of the team's task.

Although there are many dimensions (such as uncertainty, complexity, or novelty) on which tasks can vary in knowledge-intensive teams (e.g., Cohen & Bailey, 1997; Devine, 2002;

Wildman et al., 2012), we focus our arguments on *task uncertainty* as a representative boundary condition. Task uncertainty refers to unpredictability in the inputs, processes, or outputs required for the team's task (Cordery et al., 2010). When tasks are uncertain, continuous learning and adaptation are necessary to successfully complete the task. We selected task uncertainty as a representative moderator of the proposed performance relationships because it exemplifies a broader class of task characteristics that influence both the usefulness of the data on which generative AI is trained for the team's task and the extent to which collaboration among teammates is critical for successful task completion. Examples of additional task characteristics that share these properties include task complexity (Wood, 1986), task novelty (Hoegl et al., 2003), and the tacitness of the knowledge required for the task (Nonaka, 1994).

Task uncertainty occurs when some information required for the task is unavailable when the team begins working on it (Tatikonda & Rosenthal, 2000). For instance, the team may not know in advance what steps are required to complete the task, the appropriate methods to use, and the outcomes to expect (Wall et al., 2002). In contrast, when tasks are predictable, team members can more easily chart out the steps required to complete the task, identify the relevant procedures, and forecast outcomes in advance (Pearce & Ravlin, 1987). Because generative AI is trained on existing data (Vanneste & Puranam, 2024; Brynjolfsson et al., 2025), it excels at providing informational resources when it can apply patterns learned from past experience to new situations. If 'best practices' for performing a task already exist, the informational resources offered by generative AI are more likely to improve members' performance because they can help members effectively apply these practices through task augmentation. However, when tasks are highly uncertain, the best practices and exact methods for accomplishing the goal are *not* established and are thus unlikely to be included in the bank of examples on which generative AI

was trained. Because this relevant information is not accessible to generative AI models, members of teams performing uncertain tasks are more likely to encounter the limits of generative AI's abilities as they carry out their work. This logic suggests the relationship between team-level generative AI proficiency and team performance should be weaker when the team's task is highly uncertain, as the informational resources available from generative AI are less likely to support team performance.

Task uncertainty should also influence the strength of the relationship between team collaboration network sparsity and team performance because it shapes the extent to which for the loss of team cognition is costly for team performance (Pearce & Ravlin, 1987; Cordery et al., 2010; Kozlowski & Ilgen, 2006). When tasks are unpredictable, members lack knowledge about what information will be required to complete the task and what operational challenges are likely to arise during execution (Griffin et al., 2007). Under these conditions, regular collaboration among team members should be especially important for team performance because it enables members to keep their beliefs about the task up-to-date and to adapt their strategies as they execute the task (Uitdewilligen, Waller, & Pitariu, 2013). For instance, a brief information exchange might prevent one member from repeating a mistake another member just made (Argote, 2024). Conversely, when tasks are more certain (less uncertain), the absence of a shared understanding of the team's task and knowledge of how expertise is distributed within the team is less likely to harm performance because new information and adaptation are less essential to executing the task (Pearce & Ravlin, 1987; Cordery et al., 2010).

As an illustrative example, consider how task uncertainty may shape the extent to which generative AI proficiency and collaboration network sparsity affect the performance of a marketing team. When the team's task has low uncertainty – such as executing a seasonal

campaign using proven channels – generative AI proficiency should be especially useful for performance because it enables members to rapidly generate campaign copy and analyze performance metrics based on established patterns from prior years. Similarly, lower collaboration among teammates may pose little risk because the work is predictable enough that it can be easily divided up among members and completed relatively independently. Conversely, when the team's task is highly uncertain – such as developing a brand strategy for a novel product for which there is little available consumer data – the strength of these relationships reverses. Instead, generative AI proficiency may be less useful for performance because the task demands extend beyond generative AI's training data, while dense collaboration networks become more essential for members to share emerging insights, reconcile conflicting information, and collectively interpret signals about how the product should be positioned.

In summary, we propose:

Proposition 5a: *The positive relationship between team-level generative AI proficiency and performance is weaker when the team's task is highly uncertain and stronger when the team's task is highly predictable.*

Proposition 5b: *The negative relationship between collaboration network sparsity and performance is stronger when the team's task is highly uncertain and weaker when the team's task is highly predictable.*

Team Satisfaction

Finally, we suggest that collaboration network sparsity resulting from members seeking resources from generative AI rather than teammates will reduce team satisfaction by weakening affective integration among members. Management scholarship has established that opportunities for giving and receiving support at work contribute to work satisfaction (Morgeson & Humphrey, 2006). Teams provide an opportunity to develop these supportive relationships (Feld, 1981; Baldwin et al., 1997). Indeed, *affective integration* – the extent to which teammates

perceive they have high-quality interpersonal relationships – positively predicts team satisfaction (Cronin et al., 2011). Unlike team cognition, which reflects an understanding of task-focused team knowledge, affective integration reflects interpersonal closeness among team members (Stephens et al., 2013; Chen & Zhang, 2021; Seers et al., 1995). Like other emergent states, affective integration develops as a result of team experiences and serves as an input to future team processes (Marks et al., 2001; Cronin et al., 2011).

Although we argue that collaboration network sparsity will result from members seeking informational resources (rather than social resources) from generative AI instead of their teammates, we expect this shift will have spillover effects for members' affective integration because it will reduce the informal social interactions among teammates that foster positive relationships among them (Methot et al., 2021). Social interactions may accompany task-focused exchanges (Methot & Rosado-Solomon, 2019), and thus instrumental and affective relationships often coevolve within teams (Schulte et al., 2012). Consequently, shifts in how team members access informational resources carry consequences for the availability of affective resources as well. Whereas a collaborative interaction among team members may contain affective content that increases interpersonal liking and trust among members (Jones & George, 1998), interactions with generative AI do not provide similar social benefits to the team.

Although we propose that collaboration network sparsity will reduce affective integration among members, this relationship will likely be bidirectional (Marks et al., 2001). If members perceive their relationships with one another as lower quality as a result of collaborating less frequently, they may also be less motivated to collaborate when future opportunities arise (Pulles & Hartman, 2017). Thus, a feedback loop may emerge wherein members initially have fewer

collaboration opportunities to develop or maintain interpersonal liking and trust and then respond to these lower quality relationships by further reducing their collaboration.

For illustrative purposes, consider a research team working on a multi-year project. When members collaborate regularly throughout the research process, they naturally build rapport and develop mutual respect through successful work interactions (Cronin et al., 2011). These bonds make the experience of being on the team more satisfying to members. Conversely, when members collaborate infrequently because they are primarily seeking informational resources from AI, they have fewer opportunities to develop interpersonal liking, trust, and respect with their teammates. As a result, they are less likely to develop the strong affective ties that often make the experience of teamwork satisfying to members (Balkundi & Harrison, 2006).

In summary, we expect the collaboration network sparsity that results from members shifting their resource seeking to generative AI will reduce the extent to which the team provides a satisfying experience for its members.

Proposition 6: *Team-level collaboration network sparsity is negatively associated with team satisfaction due to lower levels of affective integration among teammates.*

DISCUSSION

The proliferation of generative AI presents both opportunities and challenges for teams in knowledge-intensive settings. On the one hand, team members who are skilled in working with generative AI may experience productivity gains due to their increased access to informational resources: helpful task-relevant information, advice, and feedback may be just a few prompts away. On the other hand, when teammates *substitute* interactions with generative AI for interactions with teammates, they forgo opportunities to develop team cognition that supports team performance and affective integration that fosters team satisfaction.

Theoretical Implications

The key contribution of our theory is that it conceptualizes generative AI as a substitute for collaborative interactions among teammates rather than simply a complement to individual work. Prior research suggests that the informational resources accessed through technology are complementary (rather than substitutive) of those exchanged in interpersonal interactions (e.g., Davenport & Prusak, 1998; Haas & Hansen, 2007; Leonardi & Treem, 2012; Nebus, 2006). We extend this work by theorizing that the unique features of generative AI – its ability to adapt to new tasks and instructions and to interact in natural language – distinguish it from traditional tools in its capacity to provide informational resources that are more akin to those exchanged in interpersonal interactions versus those previously available through technology. This insight challenges the teams and broader literatures on AI in organizations to treat generative AI not simply as a source of new informational resources, but as an alternative pathway through which members access informational resources they may have previously accessed through collaborative interactions with teammates and other colleagues. The possibility that generative AI redirects informational resource flows away from interpersonal channels has theoretical implications across multiple areas of teams scholarship.

Team effectiveness. An implication of our theory for the teams literature is that the possibility for members to shift their informational resource seeking interactions away from teammates and towards generative AI gives rise to competing implications of generative AI for team effectiveness. If we extend prior work that assumes informational resources from colleagues and technology are primarily nonoverlapping (e.g., Balkundi & Harrison, 2006; Haas & Hansen, 2007; Nebus, 2006), the addition of generative AI in team settings should enhance team performance by introducing new informational resources without disrupting established collaboration patterns. However, accounting for the possibility that generative AI substitutes for

collaborative interactions yields a more nuanced understanding of its impact. Teams comprised of members who are highly proficient with generative AI should achieve performance gains because efficient access to informational resources supports members' individual work. In many cases, these informational resources will complement members' efforts and function similarly to prior technologies that offered members efficiencies in carrying out their work (e.g., Haas & Hansen, 2007). Yet, when members perceive informational resources from generative AI and teammates as functionally equivalent, they may increasingly turn to generative AI *instead* of one another. This substitution behavior disrupts the team's collaboration network, constraining the development of the emergent states that underlie team effectiveness. Generative AI thus presents a dilemma for knowledge-intensive teams: Generative AI can augment team performance, but the loss of collaboration among members that results from members turning to generative AI instead of one another can offset these gains and undermine team satisfaction.

Network perspective of teamwork. The theory presented in this article also extends the network perspective of teamwork (Park et al., 2020; Crawford & LePine, 2013) and related work on organizational knowledge-sharing networks (Wang & Noe, 2010). Research adopting a network perspective tends to assume that ties among members “serve as the conduits for the flow of interpersonal resources” within a team (Balkundi & Harrison, 2006: 50). Similarly, theories of network generation characterize information technologies as ‘impersonal’ sources that do not compete directly with interpersonal interactions due to their inability to apply knowledge to specific situations or engage in two-way interaction (e.g., Nebus, 2006; Cross et al., 2001; Haas & Hansen, 2007). Although prior research has examined how technologies reshape networks by facilitating or constraining interpersonal interaction – such as making potential collaborators more visible (Leonardi et al., 2013) or limiting who can interact through algorithmic control

(Kellogg et al., 2020; Rahman, 2021; Leavitt et al., 2025) – we suggest that generative AI influences intrateam networks by affording members choice about whether to interact with technology or teammates to fulfill their informational resource needs. This argument extends the network perspective of teamwork by introducing generative AI as an exchange partner that is worthy of consideration alongside teammate ties in intrateam network studies, rather than an ‘impersonal’ source that does not compete with intrateam channels for informational resource exchange. A methodological implication of this insight is that future network research may benefit from adapting measurement approaches (e.g., asking from *whom* or *what* members seek informational resources) to provide a more complete account of the informational resource flows within teams.

Team emergent states. Finally, our theory contributes to understanding of how generative AI can disrupt the development and maintenance of team emergent states by decoupling informational resources access from informal interpersonal interactions among members. An assumption in the team emergent states literature is that team interaction processes and emergent states are self-reinforcing, such that each serves as an input to the other (Marks et al., 2001). For instance, informal information seeking (a process) influences members’ understanding of who knows what (transactive memory, an emergent state), which may then shape future information seeking (Ren & Argote, 2011). Although we do not challenge the assumption that team emergent states are the byproduct of member interactions, we propose that generative AI is poised to disrupt the informal, discretionary interaction processes that have historically supported emergent state development (Humphrey & Aime, 2014; Waller et al., 2016; Okhuysen & Bechky, 2009). A critical implication of this insight for teams scholarship is that formal team processes – such as centralized planning meetings (e.g., Lanaj et al., 2013) or

meetings to discuss goal process (Marks et al., 2001) – may be increasingly central to emergent state development in teams in which members are highly proficient with generative AI, as informal interaction processes may increasingly be redirected to technology.

Future Research Directions

Collaboration Beyond Informational Resource Exchange. Our theory focuses on the exchange of informational resources among teammates because it is central to the effectiveness of knowledge-intensive teams (Balkundi & Harrison, 2006; Park et al., 2020; Huang & Cummings, 2011). However, teammates collaborate for many other purposes, such as to set collective goals (Marks et al., 2001), coordinate the sequencing and integration of work (Okhuysen & Bechky, 2009), build status (Bendersky & Hays, 2012), and negotiate team norms (Feldman, 1984). A promising extension of our theory is to examine how the substitution dynamics we propose extend to these broader functions of collaboration. On the one hand, alternative forms of collaboration may be less susceptible to substitution because they depend on factors such as mutual recognition, shared history, and social standing among teammates. These properties are unlikely to be replicated through interactions with technology. On the other hand, informational resource exchange may serve as a gateway to these broader forms of collaboration. For instance, if members who regularly seek one another's advice also develop the familiarity and trust that enable them to negotiate norms or monitor one another's work effectively, then the reduction in informational resource exchange we theorize could have downstream consequences for these broader collaborative activities that extend beyond the scope of our model. Future research could examine whether and how the substitution dynamics we describe spill over to affect these other forms of collaboration among teammates. Investigating this boundary is theoretically valuable because it would test whether the interpersonal foundations of team

collaboration can persist independently of the informational exchanges that have, historically, sustained them.

Team Dynamics. Although our theorizing notes potential feedback loops between key constructs, we do not formally model how these dynamics unfold over time. This is a theoretically rich direction for future work, because the feedback loops we describe could create path dependence such that early substitution decisions shape the team's trajectory of collaborative behavior over time (Cronin et al., 2011). For example, because resource exchange relationships in teams tend to be reciprocal (De Jong et al., 2017), members who become asymmetrically dependent on their teammates may make efforts to become more proficient with generative AI so they too can work more independently. Longitudinal studies could examine such feedback loops and the extent to which they further reduce the team's collaboration network density.

A related promising research direction concerns team viability (i.e., team members' willingness and ability to continue working together in the future, Hackman, 1987). If teammates collaborate infrequently as a result of members shifting their informational resource seeking to generative AI, they may be less likely to develop the cognitive scaffolds that support performance in future episodes and the motivation to continue working together as a team (Bell & Marentette, 2011). Future research could examine whether teams whose members leverage generative AI frequently are less likely to persist across performance episodes.

Social networks beyond teams. The substitution dynamics we theorize within teams may also reshape the broader informal networks of information, advice, and feedback that span team boundaries within organizations (Cross & Sproull, 2004; Reagans & McEvily, 2003). For instance, members who turn to generative AI instead of colleagues in other departments for

advice may weaken the bridging ties that facilitate knowledge transfer (Cummings, 2004; Marrone, 2010). This possibility has implications for creative problem-solving, as connections to diverse contacts within the organization expose individuals to non-redundant information and alternative perspectives that stimulate creative thinking (Perry-Smith, 2006; Perry-Smith & Shalley, 2003). Unlike a colleague whose idiosyncratic experiences and expertise may surface unexpected insights, generative AI draws on patterns in its training data, potentially narrowing the range of perspectives to which members are exposed. This raises the theoretically important possibility that generative AI could simultaneously improve individuals' access to information while homogenizing the perspectives available across the organization. Future research could investigate the conditions under which employees perceive interactions with generative AI as functionally equivalent to interactions with colleagues outside their team, and how resulting substitution decisions alter the structure and creative capacity of intraorganizational networks.

Alternative forms of generative AI. The theory presented in this article focused on generative AI assistants, which represent the most common form of generative AI in today's workplaces (McKinsey & Company, 2025). However, features of the AI system itself may shape the relationships we propose in this article. For example, many firms are developing custom generative AI applications that are trained on their proprietary data (Valentine et al., 2025). Because such systems can tap into the documented institutional knowledge of the firm, members may perceive them as even more capable of providing informational resources comparable to those available through teammates, suggesting that the substitution dynamics we describe may be especially acute when members have access to firm-specific AI tools. Conversely, some generative AI applications now offer collaboration features that enable team members to share documents and make their interactions with AI visible to teammates. Such features may partially

reintroduce the social visibility of work that traditionally emerges from collaborative interactions among members, potentially attenuating the collaboration network sparsity our theory predicts. Future research could examine how variation in the design of generative AI systems strengthens or weakens the substitution dynamics at the core of our model.

Additional Boundary Conditions. The substitution dynamics at the core of our model are likely to vary in strength across different individuals and team contexts, and identifying the conditions that amplify or attenuate these dynamics is a promising direction for future research. At the member-level, factors such as members' roles (e.g., job characteristics, Morgeson & Humphrey, 2006) within the team and attitudes towards technology may shape the extent to which generative AI proficiency translates to perceived teammate-AI functional equivalence. For instance, members in roles with high information processing demands (Humphrey et al., 2007) may be more likely to perceive functional equivalence between informational resources available from teammates and generative AI because generative AI excels at tasks related to retrieving and manipulating information (Brynjolfsson et al., 2025). Members may also differ in their sensitivity to quality differences between the informational resources provided by generative AI versus teammates (Wang et al., 2024) and in their attitudes towards algorithmic technologies more generally (Dietvorst et al., 2015; Logg et al., 2019). Members who are especially sensitive to inaccurate outputs (i.e., 'hallucinations', Grimes et al., 2023) or are generally distrusting of AI systems (Glikson & Woolley, 2020) may be unlikely to perceive teammate-AI functional equivalence, even if they are proficient in using it.

Features of the team's task may also shape perceptions of teammate-AI functional equivalence. Members of teams that regularly perform uncertain tasks may be less likely to perceive teammate-AI functional equivalence because they more frequently encounter situations

in which generative AI cannot provide adequate informational resources, weakening their expectations of its utility (Vroom, 1964). Conversely, members of teams that primarily perform predictable tasks may develop stronger perceptions of functional equivalence over time as they experience repeated success in accessing informational resources from generative AI. This raises the possibility that the types of tasks a team regularly performs shape the collaboration network structures that emerge within it – and that teams whose members develop sparse collaboration networks while performing predictable tasks may struggle to reconstitute dense collaboration patterns when task demands shift.

Team-level factors beyond task characteristics may also shape the relationships proposed in our model. For example, teams with certain performance criteria – such as meeting a tight deadline (Gevers et al., 2006) – may be more likely to benefit from the efficiency gains available through generative AI (Noy & Zhang, 2023), while teams with a long history of collaboration may be less likely to require a dense collaboration network to maintain strong cognitive emergent states (Balkundi & Harrison, 2006). Similarly, teams' existing collaboration patterns at the time of generative AI adoption may influence how strongly the proposed dynamics unfold. For example, teams with sparse collaboration networks may adopt generative AI more aggressively because members have fewer established collaborative relationships to draw on, and may also experience fewer negative consequences from substitution because their cognitive and affective emergent states were already weak. Conversely, teams with dense collaboration networks may have more to lose from substitution but may also be slower to adopt generative AI as a resource. Longitudinal research that tracks teams before and after generative AI adoption would be valuable for disentangling the extent to which collaboration network sparsity and perceived teammate-AI functional equivalence operate bidirectionally.

Finally, the substitution dynamics we theorize may also be subject to contextual influences that operate above the team-level. For instance, organizational policies that mandate generative AI adoption and institute its use as a performance evaluation criterion (e.g., Marr 2025) may accelerate the development of generative AI proficiency and increase the likelihood that team members shift their collaborative interactions away from teammates and towards generative AI. Similarly, cultural influences such as strong collectivist norms (Hofstede, 2001) or tighter social expectations for relational exchange at work (Gelfand et al., 2011) could limit the extent to which perceptions of teammate-AI functional equivalence produce substitution behavior. Examining how such organizational and cultural factors shape the strength of the relationships in our model is a promising direction for future research, as it would help clarify the generalizability of our model and the contexts in which the dilemma we propose is most likely to arise.

Implications for Managers

Our theory has several implications for managers overseeing knowledge-intensive teams. First, managers should be aware that the performance benefits of generative AI adoption in team settings may be accompanied by a loss of knowledge exchange among team members. Because shifts in collaborative interactions may occur gradually – as individual members independently discover that generative AI fulfills some of the informational resource needs they previously brought to teammates – the erosion of knowledge exchange within the team may not be immediately visible to managers. Over time, however, the cumulative effect of these individual choices may weaken the team’s shared understanding of its task and diminish interpersonal bonds among members. Managers should therefore monitor not only whether their teams are

adopting generative AI, but also how patterns of collaboration among members are changing as a result.

Second, managers should be mindful that their own behavior can shape how members navigate the choice between seeking informational resources from teammates or generative AI. Leaders serve as important role models for their teams, and when managers routinely turn to generative AI for tasks they previously handled through collaboration with colleagues, they signal that substitution is appropriate, encouraging members to follow suit. By contrast, leaders who continue to engage teammates for activities such as collaborative problem-solving alongside their use of generative AI can help sustain collaboration norms within the team.

Finally, managers should carefully consider the ancillary benefit of teammate interactions before encouraging generative AI use cases that shift informational resource seeking to generative AI. Even when generative AI can fulfill the immediate functional goal of an interaction – such as providing feedback on a work product – the collaborative exchange it replaces may have served additional purposes that are not easily recovered. For instance, a software team manager who observes that generative AI provides excellent feedback on code may suggest that team members stop reviewing one another's code and turn to generative AI instead. Although doing so might achieve the short-term functional goal of successful code integration, members may fail to gain familiarity with other parts of the codebase that they do not directly maintain (Hannay, Dyba, Arisholm, & Sjoberg, 2009), making it more difficult for the team to troubleshoot in the event of a service outage or a teammate's departure. One approach to preserving these benefits is to establish structured opportunities such as regular team meetings, collaborative working sessions, or offsites where members regularly share insights

with one another and discuss lessons learned. Although many teams already hold such forums, their role may become increasingly important as informal collaboration shifts to generative AI.

CONCLUSION

A key insight of this article is that generative AI is uniquely capable of providing many of the same informational resources that have historically flowed through interactions among teammates. This potential creates a dilemma in knowledge-intensive teams: generative AI enables members to obtain informational resources that can improve team performance but can also undermine team performance and satisfaction by diminishing collaboration among team members. We hope this theory will encourage future research at the intersection of generative AI adoption and team effectiveness.

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Figures and Tables

Figure 1. A theory of generative AI proficiency, intrateam networks, and team effectiveness.

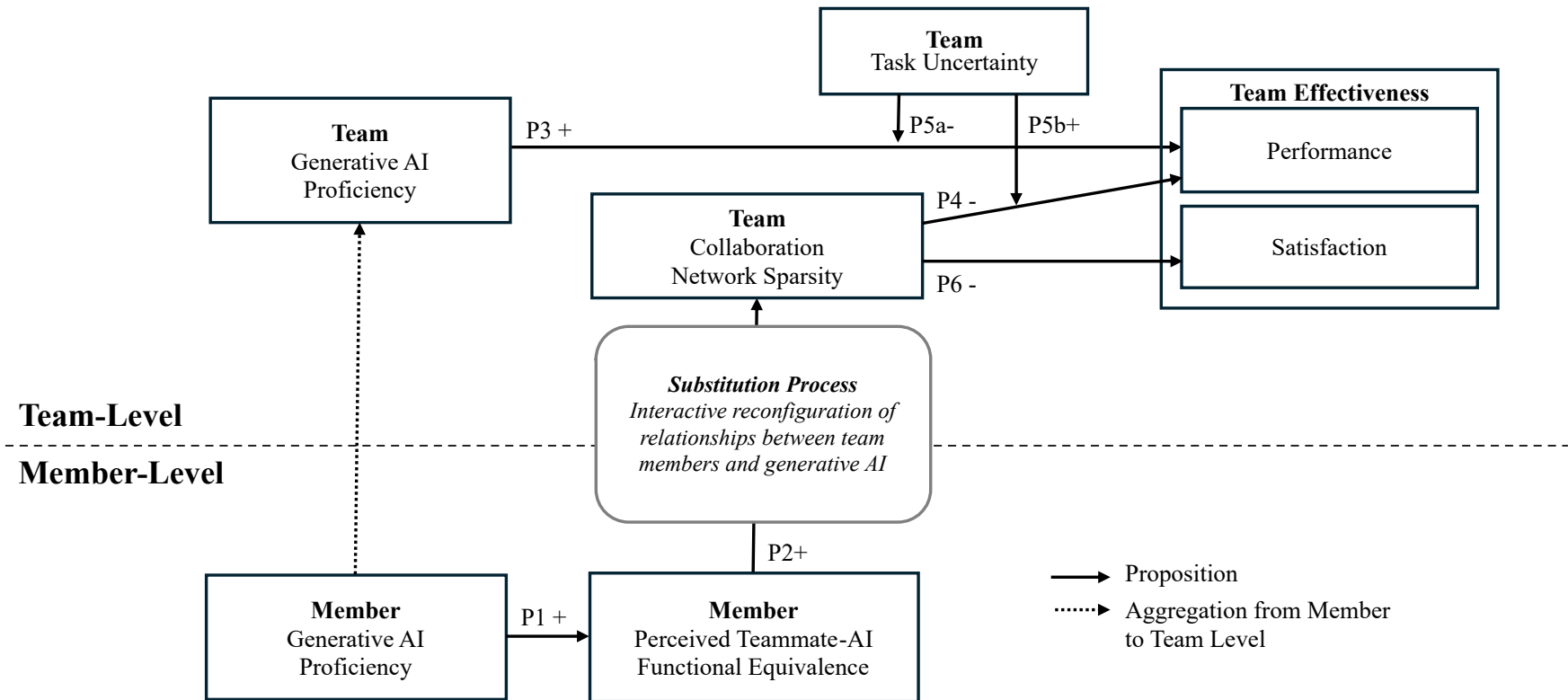


Figure 2. Example team-level collaboration networks that result from team members with higher perceived teammate-AI functional equivalence turning to generative AI instead of teammates for informational resource seeking.

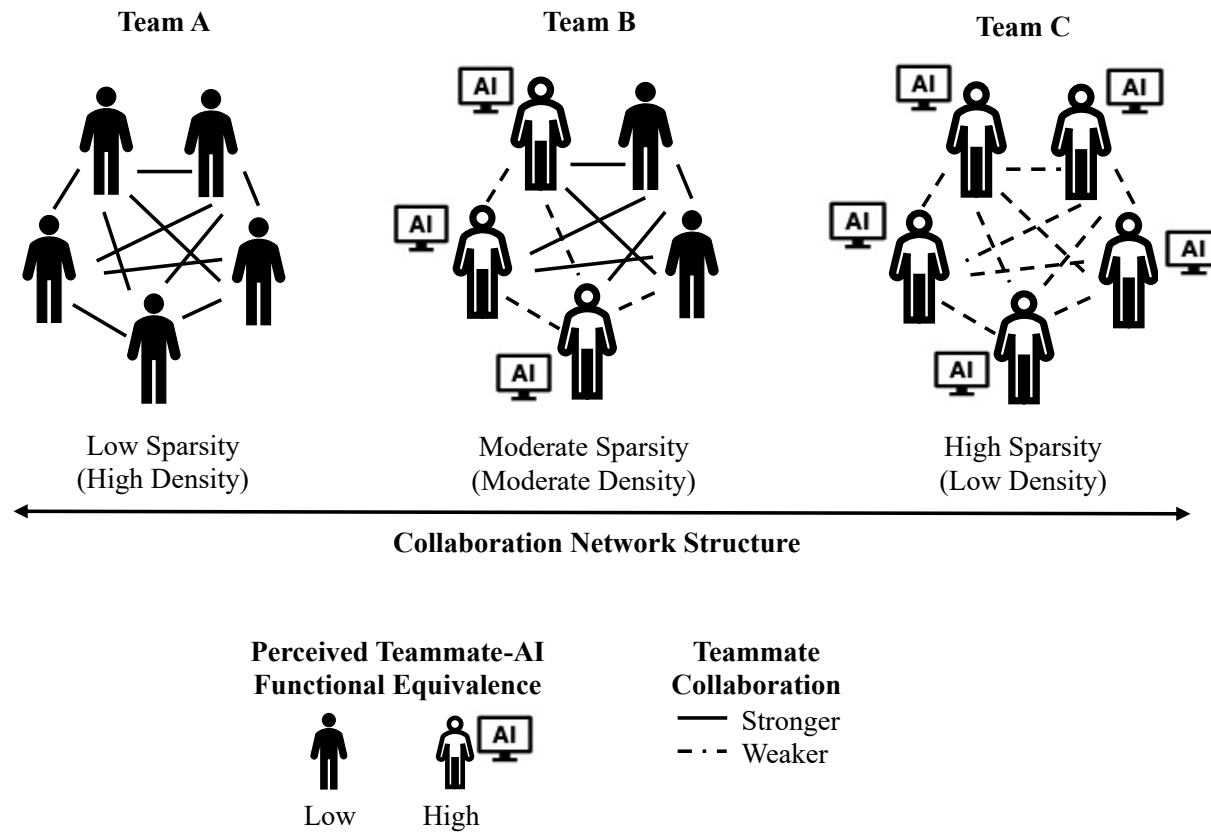


Table 1. Illustrative Examples of Information, Advice, and Feedback provided by Traditional Tools, Teammates, and Generative AI

Resource Examples	Traditional Tool Examples	Teammate Examples	Generative AI Examples
Information			
Surface and filter external information	Identify relevant websites based on search criteria (web search, Colbert et al., 2016)		
Surface and filter internal information	Retrieve relevant internal documents (database, Hansen & Haas, 2001)		
Adapt information to a members' specific use case		Apply knowledge to a specific problem (Haas & Hansen, 2007)	Apply information to a particular context or example (Dell'Acqua et al., 2026; Alavi et al., 2024)
Interpret nonroutine information		Interpret information in context (Uitdewilligen & Waller, 2018)	Retrieve information and adapt it to fulfill a specific need (Melumad & Yun, 2025)
Advice			
Provide analysis for routine decisions	Analyze routine discrete choices (decision support systems, McDonald & Ackerman, 2000)		
Predict outcomes using standard process	Make routine predictions (forecasting software, Önköl et al., 2009)		
Recommend solutions to complex problems		Support problem definition and problem-solving (Cross & Sproull, 2004)	Provide tailored solutions to an interpersonal problem (Osborne & Bailey, 2025; Rebholz et al., 2024)
Offer alternative viewpoints		Challenge or validate members' problem-solving approach (Cross et al., 2001)	Analyze a problem from an alternative viewpoint (Boussieux et al., 2024)
Feedback			
Identify errors against clear standards	Flag typos (spellcheckers, Lawley, 2016); highlight syntax errors (code debuggers, Becker et al., 2019)		
Track quantifiable progress towards goal	Visualize effort over time (dashboards, Glikson et al., 2019)		
Evaluate performance against ambiguous criteria		Evaluate performance on team activities (Handke et al., 2022)	Evaluate whether work product (e.g., writing) achieves a goal (Dai et al., 2023)
Suggest improvements when there are ambiguous criteria		Offer suggestions for how to improve project deliverables (Poltröck et al., 2003)	Provide constructive feedback on a project (Elsinger & Hörner, 2024)