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Artificial Intelligence and Groups: Effects of Attitudes and Discretion on Collaboration

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Abstract

We theorize about human-team collaboration with AI by drawing upon research in groups and teams, social psychology, information systems, engineering, and beyond. Based on our review, we focus on two main issues in the teams and AI arena. The first is whether the team generally views AI positively or negatively. The second is whether the decision to use AI is left up to the team members (voluntary use of AI) or mandated by top management or other policy-setters in the organization. These two aspects guide our creation of a team-level conceptual framework modeling how AI introduced as a mandated addition to the team can have asymmetric effects on collaboration level depending on the team's attitudes about AI. When AI is viewed positively by the team, the effect of mandatory use suppresses collaboration in the team. But when a team has negative attitudes toward AI, mandatory use elevates team collaboration. Our model emphasizes the need for managing

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team attitudes and discretion strategies and promoting new research directions regarding AI's implications for teamwork.

Keywords
group or team dynamics/processes, attitudes, technology

Much modern work is technologically sophisticated and team-based (Negoita et al., 2018; Parker & Grote, 2022). Teams can leverage AI (Artificial Intelligence) instantiated in enterprise software platforms like Wrike or Salesforce, engage with stand-alone AI (like Alexa), or travel with AI-enabled robots to disaster sites. Across settings, teams have many opportunities to work with AI—whether the team likes AI or not and whether or not AI use is at their discretion. Scholars pay increasing attention to human–AI teaming, where humans and AI work on joint tasks interdependently to achieve common goals (O'Neill et al., 2022). However, the literature leaves many basic questions unanswered. How do we support teams with AI? How will AI alter the dynamics of human teams? What drives human team members' collaboration with AI? This research thus speaks to some of the most important questions about the near-term ceiling on AI's potential in the workplace and the possibly bumpy ride for organizations during the inevitable diffusion of this technology.

Following Russell and Norvig (2021), we define AI as a digital agent that perceives its environment, adapts to change, and creates and pursues the best-expected outcome. In the context of teams, we focus on AI that exhibits some form of self-governance for decision-making, adaptation, and communication (Demir et al., 2016; Mercado et al., 2016; Myers et al., 2019). The role of AI in human–AI teams goes beyond serving as mere tools for information retrieval (Gervits et al., 2020). AI roles extend to scenarios where AI can choose or recommend a course of action that supports the team (Murray et al., 2021; O'Neill et al., 2022). Examples include locating and rescuing survivors in military situations (Ismail et al., 2020) and detecting and coordinating a medical response when a patient has fallen and needs help (Thiel et al., 2009). We acknowledge the multitude of different but related technologies (e.g., Gerlach & Cenfetelli, 2022) that make up AI applications (e.g., AI embedded in physical robots, chatbots, or hidden from view, Glikson & Woolley, 2020; Wolf & Stock-Homburg, 2022). This complexity creates a unique landscape for understanding and supporting collaboration in human–AI teams.

While individual AI applications can pose challenges, we leverage the concepts of attitudes toward AI (Lichtenthaler, 2020) and the discretion teams are allowed with AI adoption (Kellogg et al., 2020; Leyer & Schneider, 2021) to understand human collaboration with AI in teamwork. We recognize that other factors (e.g., uncanny valley, Gray & Wegner, 2012; culture, Kaplan, 2004; anthropomorphism, Wolf & Stock-Homburg, 2022) can also influence the nature of collaboration in human–AI teams. However, we focus on team attitudes toward AI because they drive a team's behavior (Del Giudice et al., 2023; Lichtenthaler, 2020). We also focus on the discretion teams have toward working with AI—whether using AI is voluntary or mandated because it drives critical organizational processes (e.g., teams' sense of control and autonomy) associated with team outcomes. Overall, even though these two factors, attitudes and discretion, are often independently linked to technology adoption (Heidenreich & Talke, 2020) and teams' success (Musick et al., 2021), we believe it is essential to understand how they jointly influence collaboration and the nature of those effects.

To advance our understanding of how AI use changes teams, we first review a body of work relevant to attitudes and discretion to inform and guide our theorizing (Patriotta, 2020). We then connect research findings across different disciplines to provide a new perspective (Post et al., 2020) and offer insights (e.g., asymmetric effects based on team attitudes) into the emerging phenomenon of human–AI collaboration. We draw on research from groups and teams, social psychology, information systems, engineering, and other areas to develop a team-level conceptual framework. The framework addresses the diverse findings related to what we know about team attitudes, discretion, collaboration, and AI.

On a practical level, we aim to inform the design of future AI-group policies and organizational practices. Such policies could guide the recruitment and selection of group members to interact with AI and help identify risks and opportunities for human–AI groups collaborating in organizations. More importantly, such policies can guide the level of AI discretion teams have to maximize collaboration or constrict it. We also account for the continually evolving role of AI in groups and teams in response to technological progress that is far faster than traditional social science. We evaluate findings across different fields (Alvesson & Sandberg, 2020) and investigate effective collaboration between humans and AI working as teams. Leaders, managers, group members, and technology designers need a framework to leverage AI effectively in team environments.

AI in Teams: Definitions

Rich AI Landscape

The increasing use of AI makes understanding the interactions between humans and AI, and the implications for team processes, of critical importance (R. Zhang et al., 2020). We started with a search for "Artificial Intelligence" articles on Web of Science to identify the most highly cited papers across disciplines and then in business journals only. Then we used VOSviewer to visualize the main terminologies in the AI literature and their relationships. We see in Figure 1 that AI research in all fields has primarily focused on the *creation* of AI, with main terms such as "accuracy," "deep learning," and "sensitivity." However, narrowing the search to the business field only (see Figure 2), we see that this research, while also exploring similar terms such as "prediction," is more focused on the *use* of AI with terms such as "performance," "service," and "price." These data reflect the relevance of our topic to the study of groups and teams. Existing research concerning AI collaborating in groups seems also limited or fractured at best.

AI comes in many forms. Glikson and Woolley (2020), for example, differentiate between robotic, virtual, and embedded AI in their review of human trust in AI. Embedded AI is largely invisible to human actors, existing within a broader tool. Virtual AI display as text (e.g., chatbots like ChatGPT).

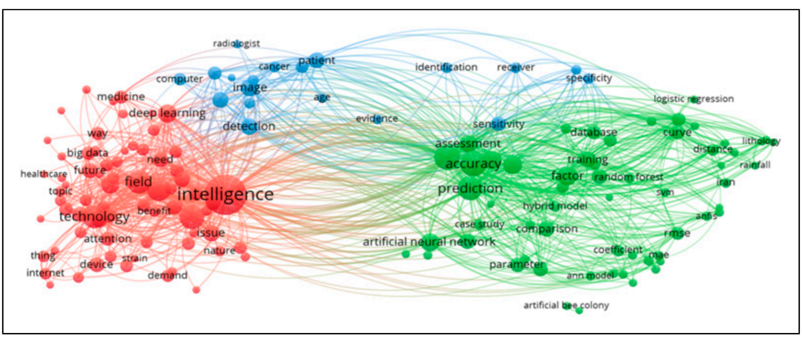

Figure 1. Terms in recently published highly cited AI articles across all fields*.*Figure 1 illustrates terms in the most highly cited 465 AI articles published between 2015 and 2020. Each circle reflects a term, with the circle's size indicating how frequently the term appears in these articles. Terms in the same clusters have the same color. The links among the terms show co-occurrence of the terms within single articles, and the proximity of the terms provides an estimate of how related the terms are.

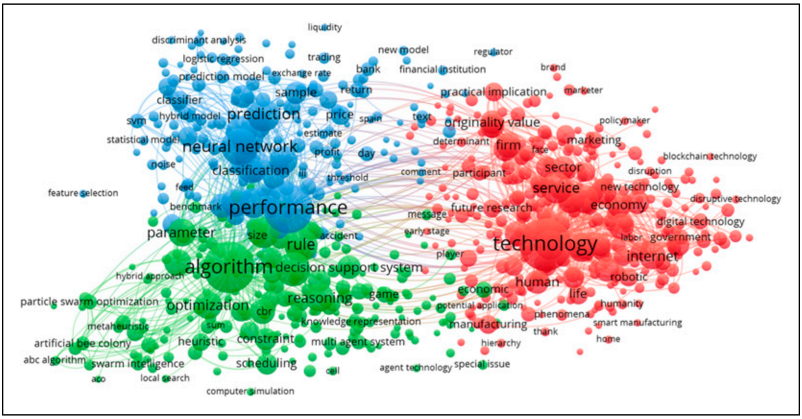

Figure 2. Terms in AI articles published in business journals.*Figure 2 illustrates terms in 759 AI articles published in business journals before 2021. Each circle reflects a term, with the circle's size indicating how frequently the term appears in these articles. Terms in the same clusters have the same color. The links among the terms show co-occurrence of the terms within single articles, and the proximity of the terms provides an estimate of how related the terms are.

Robotic AI is embodied in a physical robot. Wolf and Stock-Homburg (2022) take on this last class of AI in their review of human–robot teams. Specifically, embodied robots are "physical representations of AI in a physical world that recognize their environment and can interact with it" (Wolf & Stock-Homburg, 2022, p. 2). Both Glikson and Woolley and Wolf and Stock-Homburg find that the form of AI, as well as the capabilities of the AI (how intelligent it is), serves as antecedents to human cognitive, emotional, and behavioral reactions.

We offer Figure 3 to acknowledge the possible richness of the AI embodiment and the roles AI may play in teamwork now and in the future. We say possible, as this richness may not be apparent to all users. For example, AI may or may not support a particular driving/mapping tool, and the technology users may or may not understand the embedded technologies behind the mapping interfaces they see (e.g., not understanding whether traffic routing is real-time or based on historical averages). Whether or not people have a correct or complete understanding of the technology in question, it is within the bounds of our model if they perceive the technology as intelligent with partial or high levels of autonomy (e.g., O'Neill et al., 2022).

Given our focus on human perception and interaction with AI, we parallel Glikson and Woolley in considering artificial intelligence from the users'

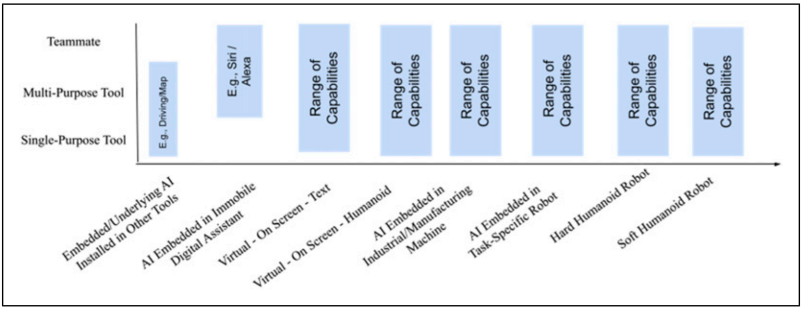

Figure 3. Span of the AI-team landscape.

point of view versus an engineering perspective based on actual technological capabilities. Griffith (1999) notes that designers build technologies from available features—whatever the current state of the art, both known/acknowledged and unknown/unacknowledged. Users understand technology features based on what they perceive (or not), use (or not), and even create on their own.[1] This process is recursive as the state of the art changes, designers adjust based on user actions, and users gain experience. In the case of AI and teams, we acknowledge that this is a fuzzy boundary. Especially in this early research stage, we must highlight the fact and the perception as we dig into empirical work. Such careful research offers better foundations and may illuminate important areas for deeper examination (Korosec-Serfaty et al., 2022; Orlikowski & Iacono, 2001).

As a start to this increased specificity, we acknowledge the various roles that AI can play in teamwork. Most simply, AI can have a particular focus (e.g., a mapping tool). At the other extreme, we see AI as a teammate, where the AI exhibits some form of self-governance with respect to decision-making, adaptation, and communication (Demir et al., 2016; Mercado et al., 2016; Myers et al., 2019) within the team. AI can be embedded in physical or virtual tools, as noted in Figure 3, but AI can also be static or dynamic in its learning and responses (e.g., Joshi, 2020). Where AI is dynamic, we are pushed beyond what we can generalize from decades of groups and teams research (and regulatory regimes, e.g., USFDA, 2021). Prior work focused on less intelligent technologies (e.g., fixed automation, algorithms, and tools built with AI but not dynamic in their implementation, c.f., L. Larson & DeChurch, 2020). As noted above, AI in human–AI teams are more than mere tools for information retrieval (Gervits et al., 2020). Instead, we see scenarios where AI can choose or recommend courses of action (Murray et al., 2021; O'Neill et al., 2022).

Teams and Team Collaboration

In a review of a century's worth of team research, Mathieu and colleagues (2017) summarized teams as "an arrangement of people brought together to accomplish one or more common goals…." (p. 461). The scholarly definition of teams, however, is shifting. Wageman and colleagues (2012) foreshadowed our use of adaptive, self-governing AI in teams by noting that "...the very notion of a traditionally defined 'team' may become increasingly outmoded" (p. 301). Research spanning the groups and teams literature (e.g., Wolf & Stock-Homburg, 2022), information systems (e.g., Seeber et al., 2020), and other fields (e.g., O'Neill et al., 2022) allow for team roles held by AI. We see examples of these in military applications, such as scouting and reconnaissance (Ismail et al., 2020); disaster relief applications, such as urban search and rescue (Murphy, 2004); and assistive applications, such as medical care (Thiel et al., 2009). Humans are increasingly dependent on AI because of its advanced capabilities to perform various tasks across numerous domains (National Academies of Sciences, Engineering, and Medicine, 2022).

The most recent of this research, Wolf and Stock-Homburg's (2022) review, offers a foundation. They take on embodied robots powered by AI (versus our focus on AI more generally) and conceptualize collaboration between humans and AI as a team process that positively affects team effectiveness. Thus, we bound our modeling on human–AI teams consisting of at least two human members and at least one AI, all working on joint tasks interdependently to achieve common goals. This collaborative work, extending from Negoita and colleagues (2018), as is with collective activity across humans, can vary across more and less siloed, processual, coalesced, and networked activities.

We also focus on AI that can choose how to communicate, adapt, and make decisions within the team (Mercado et al., 2016; Myers et al., 2019). Considering Murray and colleagues' (2021) 2 × 2 across locus of agency in protocol development (human/technology) and locus of agency in action selection (human/technology), we include their augmenting, arresting, and automating forms, but not assisting. They note that assisting technologies are non-agentic and are "wielded by humans in both protocol development and action selection" (p. 553). We code that form as a tool rather than a teammate.

We acknowledge a special role for humans "in the loop," given the possibility of grave errors at this stage in AI development (A. Gupta et al., 2021) and the value of deep human domain expertise (Sturm et al., 2021). Human team members can be in the loop for the design/redesign of AI systems and auditing (Grønsund & Aanestad, 2020). Research on delegation to and from agentic technologies is in its early stages, focusing on human–technology dyads (e.g., Baird & Maruping, 2021). Baird and Maruping (p. 336) highlight open questions, including "how will balance be achieved between individual and collective needs, especially as the number of interacting agents grows?"

For AI and humans to work effectively as a team, they need to integrate their individual actions successfully: human–AI teams need to collaborate. Collaboration is a key team process for enhanced team effectiveness (DeChurch et al., 2013). Collaboration refers to the collective process of members converting their inputs into team products (LePine et al., 2008; Yuan & van Knippenberg, 2022; Zaccaro et al., 2001). For example, team collaboration can manifest in how well team members share task understandings and strive to achieve team goals (Yuan & van Knippenberg, 2022). Characteristics of team collaboration include open discussion of diverse perspectives and the team's commitment to coming up with solutions that benefit the team as a whole (DeChurch et al., 2013). Overall, team collaboration is a synergistic process of integrating diverse resources and viewpoints into team products.

We focus on collaboration's first stage: engagement as an AI-team process. Engagement parallels the first phase in a technology implementation process (Bayerl et al., 2016) and the first step in a team's developmental processes (e.g., N. L. Larson et al., 2020). In the engagement stage, collaborating team members initially come together and become aware of the team's composition and "first-order understanding" of key capabilities necessary for cooperation (Dafoe et al., 2020). Specifically, initial team-level collaboration, engagement, can be observed as "meaningful participation" (Janssens & Brett, 2006)—members do not necessarily contribute all the time, but rather when they have a meaningful contribution to make (Crotty & Brett, 2012). We find this a valuable distinction given people and AI may not have value to add at all times. The careful consideration of this meta-processing may be especially valuable in human–AI teams. Indeed, other team processes (e.g., communication, interdependence, and transactive memory) are critical aspects of group and team outcomes (Bachrach et al., 2019; Courtright et al., 2015). However, without this first collaborative stage, there are no deeper interactions.

Literature Review

We take what Post and colleagues (2020) call a generative approach to reviewing to develop a new model, framework, or other unique contribution (Torraco, 2005; 2016). We draw on a stream of recent influential reviews across different disciplines to guide our theorizing and choice of context and key constructs (e.g., team collaboration, human–AI teams). These reviews informed us about the determinants of human trust in AI (Glikson & Woolley, 2020), discretionary use of AI (Nickel, 2022), human–robot teams (Wolf & Stock-Homburg, 2022), human–autonomy teaming (O'Neill et al., 2022), and overall challenges and opportunities posed by the rapid emergence of AI across multiple domains (Dwivedi et al., 2021), including in the context of long-duration spaceflight (c.f., Zumbado et al., 2011). Two themes emerged based on this initial review: attitudes toward AI in general and teams' discretion in using AI.

We then tackle "an emerging issue that would benefit from exposure to potential theoretical foundations" (Post et al., 2020, p. 369) by diving deep into specific literatures connected to attitudes, discretion, and human–AI teams. Our intuition is that team members' pre-existing attitudes toward AI and the discretionary nature of AI may influence their engagement with AI in the team. We thus adopted the approach of using an expansive list as some valuable background research comes from topics other than our specific focus. This approach allows us to acknowledge differing perspectives on how the roles of intelligent agents, less intelligent algorithms, AI, etc., differ in team use and outcomes (Jussupow et al., 2020; L. Larson & DeChurch, 2020; Sycara & Sukthankar, 2006; Wolf & Stock-Homburg, 2022).

We began with a database search (e.g., PsychINFO, IEEE Xplore, Compendex, Education Resource Information Center (ERIC), Business Sources Complete, EBSCO, and CNKI) to inform our theoretical model and capture relevant articles across disciplines. While we focus on AI, teams, and collaboration, we also included "groups," "collectives," "interaction," "human," and combinations across "artificial intelligence," "AI" and "attitudes," "AI" and "mandatory," "AI" and "voluntary," "AI" and "discretion," as well as extensions, including "algorithms," "robots," "robotics," and "intelligent machines." While some of these terms are broader than our AI definitions, we started with this broader set to build stronger foundations for studying this emergent phenomenon. Additionally, we tracked citations to identify other appropriate research missed with our initial search.

Through this process, we captured relevant articles across multiple disciplines to determine the implications of AI for group collaboration. These included empirical and non-empirical work, review papers, qualitative studies, measurement articles, book chapters, and theory pieces. We identified multiple disciplines in our review of the literature showing how the concepts we discuss have a broad appeal across many domains (e.g., management, information systems, engineering, communications, computer science, and ethics). Social psychology (e.g., team attitudes), information systems (ISs—voluntariness, discretion, mandatory use), and groups and teams (human–AI teaming, including collaboration) substantially contributed to our theory building. Computer science, engineering, and related technical fields offer empirical examples and perspectives related to features of AI used in teams but less about attitudes and discretionary use.

Attitudes Toward AI

We next focus on the attitudes of teams toward AI. Given the early stage of team application of AI, we primarily build from research on individual attitudes in teams and individual attitudes toward AI. Research on AI implementations notes that individual attitudes and perceptions toward AI play a vital role in determining success (Chatterjee et al., 2021; Reis et al., 2020). For instance, individual attitudes toward AI predict people's trust (Hancock et al., 2011), openness (Lichtenthaler, 2020), and intention to use AI (Young et al., 2021), all of which are essential for effective collaboration with AI teammates. Research on traditional technology use (e.g., information/communication technology, Bayerl et al., 2016) at the team level also highlights the value of understanding the role of attitudes. We draw on literature from social psychology but note that attitudes attract attention from other disciplines as well (e.g., information systems: Bhattacherjee & Premkumar, 2004; Cao et al., 2021; Davis, 1989; Kroenung & Eckhardt, 2015; Venkatesh et al., 2012).

Individual attitudes have long been a major focus in social psychology research because of their assumed predictive power on people's behaviors (Ajzen et al., 2018). Eagly and Chaiken (1993) describe an attitude as "a psychological tendency that is expressed by evaluating a particular entity with some degree of favor or disfavor" (p. 1). The entity can be something, someone, or even an abstract idea (Albarracín & Shavitt, 2018). For instance, job attitudes describe employees' evaluation of their job, which can impact job satisfaction, engagement, and organizational commitment (Judge & Kammeyer-Mueller, 2012, p. 344). Central to our conceptual framework are collective evaluations of AI as good and beneficial for the team (positive attitudes) or bad and unhelpful (negative attitudes).

Some prior research adopts a tripartite model of attitudes, separately considering cognition, affect, and behavior (Breckler, 1984). Others reserve the term attitude only for evaluative tendencies (Albarracín et al., 2005). In their 2018 *Annual Review of Psychology* piece, Albarracín and Shavitt (2018) say, "the attitude-behavior relationship is best seen as an empirical question outside of the definition of attitude, a definition that simply focuses on the evaluative nature of attitudes as favor or disfavor" (p. 300). For the sake of parsimony and given our focus on behaviors within AI–human teams, we work with this relatively simple definition rather than the tripartite model. This simplicity is also helpful in that we examine the role of attitudes toward AI at the group level rather than individually (e.g., Bayerl et al., 2016).

Consistent with the somewhat limited prior research on group adoption of technology (Bayerl et al., 2016; Hartwick & Barki, 1994; Sarker & Valacich, 2010), we define a team's attitudes toward AI as the extent to which a team collectively feels the AI is evaluatively good or bad. People may evaluate the AI via its level of autonomy in decision-making (Komiak & Benbasat, 2006; Nissen & Sengupta, 2006), perceived capabilities (Longoni et al., 2019), usefulness (Davis, 1989), or social and emotional interactions with AI (Syrdal et al., 2009). We, for two reasons, focus on overall evaluative attitudes in our model instead of specific components or more specific attitudes toward particular features (Griffith, 1999) of the AI. First, given the early stages of the research and the complexities involved in judging AI as a teammate, we believe staying at this higher level will be more fruitful for generalizability. Second, the mutability of AI: today's AI may not be the AI of tomorrow, so a broader focus provides a better foundation.

Research on attitudes related to acceptance of AI in workplace settings is on the upswing (e.g., Luchini et al., 2022; McKinnel et al., 2019; Peres et al., 2020; Vlačić et al., 2021). Nevertheless, this research focuses primarily on individual-level attitudes and has not provided much clarity or consensus for group collaboration with AI. Essential questions and themes about team-level attitudes toward AI come from this literature, such as the idea that "extreme attitudes could emerge in the same group of people" (Lichtenthaler, 2020, p. 43). While some groups resist AI, others readily accept and leverage it (based on evidence from earlier non-AI technology, e.g., Maruping & Magni, 2015). Overall, we do not yet fully understand the role of team attitudes in the context of AI.

Attitudes Toward AI: Negative

Results of multiple national surveys find negative attitudes toward AI dominating in the overall population. For example, a survey conducted in the UK (Cave et al., 2019) showed negative views of AI; 61.8% of the respondents also felt that they could not influence how AI will develop in the future. Similarly, in a US sample (B. Zhang & Dafoe, 2019), 34% responded that AI would have a net harmful impact. Moreover, these negative attitudes also appeared to differ by demographic characteristics; men and people with college degrees and higher incomes exhibit fewer negative attitudes. Consistent with these findings, but in the healthcare context, people trust doctors and accept their treatment recommendations over those of AI (Yokoi et al., 2021). Additionally, an anthropological field study and four experiments found that participants had more negative attitudes toward a robot nurse forcefully medicating a patient than a human nurse (Laakasuo et al., 2019).

Among the literature on individuals' attitudes toward AI, the research on algorithm aversion is an active area (e.g., Burton et al., 2020; Mahmud et al., 2022). A key finding in this research (a broader topic than attitudes toward AI teams as it includes all forms of algorithms[2]) is that people across various domains often choose human advice/decisions over those given by algorithms, despite demonstrations of higher accuracy from algorithms (Dietvorst et al., 2015). People may blame algorithms for an inability to learn (Dawes, 1979) and a presumed ability for human forecasts to improve over time (Highhouse, 2008). An ideology that algorithms are dehumanizing may also be a source of aversion (Dawes, 1979; Grove & Meehl, 1996).

Because the antecedents of AI attitudes are not our current focus, we provide a relatively brief review of what may contribute to negative attitudes toward AI. Antecedents can include people's aversion to AI-enabled tools (Mahmud et al., 2022), fear of job loss (Vu & Lim, 2022), lack of trust in AI (Solberg et al., 2022), a lack of personal relationship with the company and work environment (Möhlmannn et al., 2021), or design features of AI (Roesler et al., 2022). Research also considers whether individual negative attitudes regarding AI come from the perception that AI lacks a "complete mind." From a philosophical perspective, "mind" is often considered a prerequisite for moral decision-making (Bigman & Gray, 2018). Consequently, individuals are likely to evaluate AI as negative and bad because it does not have "the ability to freely choose actions…and the ability to appreciate the consequences of one's actions" (Bigman & Gray, 2018, p. 22).

Attitudes Toward AI: Positive

Despite the apparent dominance of individual negative attitudes toward AI, positive evaluations are also in evidence. For instance, Wang and colleagues (2019) surveyed data scientists on their attitudes toward AI systems automating data science projects and found data scientists remain optimistic about a collaborative future with such technologies. Scott and colleagues (2021) find favorable evaluations in some healthcare settings, especially among those with direct experience with AI. Additionally, some individuals evaluate AI competency as superior to human experts. For example, computer science graduate students favor an image processing agent over an expert graphic artist (Williams et al., 2019), and medical residents prefer when an AI schedules their rotations (F. M. Howard et al., 2020).

Positive AI attitudes appear to be rooted in individual digital technology efficacy (Vu & Lim, 2022), perceived ease of use and usefulness (Fan et al., 2020), and design as assistant (versus a friend, Kim et al., 2021). In addition, Yam and colleagues (2022) note that people perceive AI more positively to the extent that they view AI as having agency and the ability to feel. This last is especially interesting as it goes beyond results related to more traditional, static technologies.

Attitudes are complex and difficult to capture (Albarracín & Shavitt, 2018). Yet, the human ability to access attitudinal assessments and then the stability of those assessments is critical to our understanding of how attitudes connect to behaviors (Glasman & Albarracín, 2006; Kroenung & Eckhardt, 2015). Specifically related to AI, attitudes may play a role in trust evaluations (Glikson & Woolley, 2020; Tussyadiah et al., 2020) and willingness to team with AI (drawing from multiplayer online games, R. Zhang et al., 2020).

AI Discretion: Voluntary or Mandatory?

Beyond team attitudes toward AI, a major consideration in human–AI team collaboration is whether AI is introduced as a mandatory part of the work process or something a team elects to use. Research spanning traditional technologies (e.g., Lin & Shao, 2000; Tsai et al., 2017) and AI implementations (e.g., Ochmann et al., 2021) points to the importance of discretion in implementation outcomes. Although many other factors are likely at play (e.g., top management support and culture), we first look at how information systems (ISs) literature considers voluntariness (Hartwick & Barki, 1994; Jasperson et al., 2005) and discretion (G. S. Howard & Mendelow, 1991). Again, given limited research at the group level, the review draws on research at the individual level of analysis, highlighting the opportunity for greater focus on group-level work.

The technology acceptance model (TAM) influences our focus on the voluntariness of adoption. Ghazizadeh and colleagues (2012), for example, consider the role of voluntariness in automation implementations. Looking back to TAM (e.g., Davis, 1989), Ghazizadeh and colleagues highlight the likely differing effects of perceived ease of use and usefulness (see also Venkatesh & Davis, 2000) given mandatory versus voluntary applications. The role of voluntariness is also a critical factor identified in Wu & Lederer's (2009) meta-analysis of technology use. Organizations adopt AI and other technologies, expecting employees to use them. Acceptance and use, of course, are not guaranteed, as evidenced by numerous reports of implementation failures (Klein & Sorra, 1996). Thus, understanding the role of discretion in AI implementation is key to appreciating the process by which groups will use AI and the outcomes accrued.

Another reason we focus on discretion is that discretion is a primary design factor in other areas of organizational procedures, practices, and interventions—for example, whether training programs are voluntary or a required part of organizational processes (Bezrukova et al., 2016). Leyer and Schneider (2021) note that whether organizations introduce AI as a voluntary intervention or a requirement can lead to managers perceiving their abilities as enhanced or as suffering a loss of power and discretion (it was not clear which of these outcomes would be the most common in workplaces). We draw on job design theory generally (autonomy, specifically) and power relationships to appreciate the potential impact of the voluntary/mandatory choice. We focus on how much discretion a team has and discretion's connection with job design. The literature has yet to thoroughly examine how technology, especially AI-driven interventions, affects these processes (Parker & Grote, 2022).

AI may (or at least may be perceived to) remove discretion from operating employees or managers (Prunkl, 2022; Raisch & Krakowski, 2021), likely impacting the perceived autonomy associated with the job. Prior research suggests that the level of autonomy and its relationship with technology can have serious implications for team collaboration and other attributes of work (Parker & Grote, 2022). The implications of the voluntariness dimension (or discretion), specifically for team collaboration, especially concerning AI, remain largely unsettled. Based on studies in other realms (e.g., training) and meta-analysis regarding technology adoption (Wu & Lederer, 2009), we see that discretion is a significant factor. Considering the role of discretion is a crucial piece of how team members might, or might not, collaborate with AI (Ochmann et al., 2021).

We view discretion based on Tsai and colleagues' (2017) review and synthesis across the broader and longer-standing information technology (IT) literature. While the theme of discretion emerges from our AI-focused literature review, the nuance of the broader IT field offers value. Tsai and colleagues (2017) cast a wide net for their review using "discretionary," "voluntary," "volitional," "mandate," "required," and "mandatory" to identify appropriate research. Their model highlights the well-known cognitive conceptualization of perceived voluntariness (Moore & Benbasat, 1991) and environment-based voluntariness (Wu & Lederer, 2009). In our paper, we draw on environment-based voluntariness—what Tsai and colleagues (2017) call "intended" voluntariness—whether or not use is directed via organizational policies/mandates.

Voluntary AI. To summarize this section, we clarify how an organization's decision to use AI as voluntary affects felt autonomy, motivation, and responsibility of employees. Consistent with Tsai and colleagues (2017), we view voluntary, discretionary use of AI as one of the factors that can influence team behaviors. Voluntary use occurs when teams have the option to decide to use the technology or not (Leonard-Barton & Deschamps, 1988). Conceptually, voluntary use of AI is hypothesized to influence behavior directly (e.g., Chen et al., 2015; Hester, 2011; Higgins et al., 2007) and also indirectly (Belanche et al., 2019). However, empirical findings regarding the voluntary use of AI remain inconsistent, yielding positive, negative, and no support for most of the hypothesized relationships (e.g., Hester, 2011; Higgins et al., 2007; Hsu et al., 2007; Templeton & Byrd, 2003). For example, research shows that the use of technology at work depends on deliberate actions and a voluntarily made decision to use it (Ahuja & Thatcher, 2005; Jasperson et al., 2005). Voluntary use of AI is related to behavioral intent to use (Karahanna et al., 1999).

Assuming use was voluntary, Zamani and Pouloudi (2021) tried to identify underlying mechanisms that lead users to different responses to AI and other technologies, such as working around it or revising the process. They concluded, consistent with the model in the present study, that having or maintaining a sense of control over the work is a rationale for modifying work process, or in general, finding a desired task-technology fit (Beaudry & Pinsonneault, 2005). Also, Karahanna and Agarwal (2006) support the idea that potential motivation is needed for users to explore technology in a voluntary setting as they will expend significant cognitive resources. Abubakre and colleagues (2015), focusing on the case where use is voluntary, consider behavioral and outcome controls as a counterweight to employee resistance to technology. The more people perceive adoption as voluntary, the stronger the link between attitudes about use and actual use. In this paper, we consider how the voluntary use of AI could amplify or suppress the effects of a team's attitudes toward AI on overall team collaboration.

Mandatory AI. Whether organizations mandate AI use or offer discretion may be constrained by technical design. Mandatory use of AI requires teams to use specific technology, denying the option to perform the task without this technology (Brown et al., 2002; Ochmann et al., 2021; Venkatesh & Davis, 2000). On the one hand, mandating AI may signal an organization's commitment and support for AI from top management (Alsheibani et al., 2018; Jöhnk et al., 2021). Yet, taking choices away from people may engender resentment (Ferneley & Sobreperez, 2006; Lapointe & Rivard, 2005). Research in organizational behavior and job design posits that mandatory technology use is related to a lack of autonomy and job control (Parker & Grote, 2022). Lack of perceived autonomy is related to a multitude of important workplace outcomes like motivation and performance (Hackman & Oldham, 1976), anxiety and stress (Karasek, 1979), and more (Parker & Grote, 2022).

The idea that mandatory use of AI plays a critical role in acceptance of new technology such as AI seems clear. Yet, the manner and mechanism by which these dynamics exert their effects is less clear. Some research theorizes mandatory use as an independent variable (Chen et al., 2015; Hester, 2011; Higgins et al., 2007), but other models see it as a moderator (Venkatesh & Bala, 2008) affecting behavior. The empirical results come up short in settling the issue of mandatory use and its place; we have positive, negative, and non-significant results across studies (Tsai et al., 2017). Some suggested mandatory use could signal organizational commitment and empower people to explore and adopt technology (Vassileva & Palamarova, 2021). Still, others propose continued study of psychological reactance, cognitive dissonance, and loss of decisional control for understanding responses to mandated use (Heidenreich & Talke, 2020). The takeaway for mandatory use is that its effect on collaboration could be felt through employee reactions to the mandates, signals sent by management that collaboration with AI is critical for the business, or a combination.

Theoretical Propositions

As noted above, considerable attention is given to the idea that AI can be a full-fledged teammate (Seeber et al., 2020; G. Zhang et al., 2023), yet researchers differ in their assessments of how realistic the notion of an AI teammate is. Some suggest that human–AI teamwork is our current reality (L. Larson & DeChurch, 2020; McNeese et al., 2021), whereas others argue that AI still lacks the full situational and social awareness necessary for teamwork with humans (Beans, 2018). We next use our review to develop a theoretical framework and clarify what drives team members' collaboration with AI in human–AI teams. More specifically, from our literature review, we identified key factors (AI attitudes and AI discretion) and now synthesize prior research across conceptual levels to develop specific propositions. Table 1 summarizes our theoretical rationale and proposed effects for team collaboration. Some of our predictions are straightforward; others are less obvious.

Negative Attitudes Toward Discretionary AI

It is likely that, given discretion, a team negatively inclined toward AI will not engage with the AI if they have the choice (see Table 1). Research shows that

Table 1. Summary of Proposition.

Attitudes Discretion	Negative	Positive
Voluntary use	- Proposition 1 - Key citations: Bigman & Gray (2018); Rice et al. (2019) - Rationale: Resistance to collaboration - AI–human engagement: *Lowest*	- Proposition 3 - Key citations: Hwang et al. (2016); Lichtenthaler (2020) - Rationale: Openness to collaboration - AI–human engagement: *Highest*
Mandatory use	- Proposition 2 - Key citations: Vassileva & Palamarova (2021); Hartwick & Barki (1994) - Rationale: Organizational commitment will counter resistance - AI–human engagement: *Medium*	- Proposition 4 - Key citations: Heidenreich & Talk (2020); Feng et al. (2019) - Rationale: Threat to freedom and control will counter openness - AI–human engagement: *Medium*

negative attitudes toward AI drive a lack of engagement across many contexts, such as making moral decisions (Bigman & Gray, 2018) or willingness to fly in a pilotless plane (Rice et al., 2019). Negative attitudes toward AI technology can be rooted in a lack of trust, where a team associates AI with something they cannot learn or understand (Dawes, 1979). Or, people may fear errors and mistakes that may harm individuals in the team or collectively (R. Zhang et al., 2020). Astronaut John Glenn's request to "Get the girl to check the numbers" is a historical illustration of how distrust can play out in terms of engagement. Glenn was referring to NASA mathematician Katherine Johnson, who calculated orbital trajectories for Glenn's Mercury flight in 1962 to check the computers used at the time (Shetterly, 2016).

One might anticipate several alternatives to engagement with AI for teams with discretion. Yet, the end result stays the same—some groups may avoid technology altogether (e.g., Talke & Heidenreich, 2014). Rice and colleagues (2019) found that 60 percent of people are unwilling to fly in an automated plane and will keep flying with a pilot until that option is no longer available. In voluntary AI scenarios, teams' negative attitudes toward the AI can exert full control over their decision and thus simply choose not to engage or collaborate with the AI.

Turning to another human–AI example, imagine a search and rescue team that has an AI-enabled "dog" robot available in their van. In the instance of negative attitudes toward the robot and discretion regarding how to work with it, when they go on a mission following an earthquake, we expect the humans to leave the "dog" in the van when they reach the search site. Possessing this discretion to decline using AI conveys felt autonomy to employees (Leyer & Schneider, 2021), a key motivating factor for choosing not to engage or expressing a preference for other options.

Another example where a team can decline engagement could be a chatbot AI available to a supply chain team. The chatbot notices a storm coming that will disrupt shipping times. The chatbot offers the team alternative routing. The humans may not engage at all, ignoring the weather warning and suggested routing. Without such engagement, there is no human interaction with AI, and the AI never gets a chance to offer value. Thus, if the team has negative attitudes toward AI and has some discretion for using it (i.e., use is voluntary), we anticipate the lowest level of team collaboration with AI will result (see Table 1).

Proposition 1. *(P1):* Teams with negative AI attitudes that can voluntarily use AI will have the lowest levels of engagement with AI.

Negative Attitudes Toward AI and Mandated Use

Teams with negative attitudes toward AI are likely, at the outset, to have little trust in it, especially in performing important team tasks (Ong et al., 2012). Such unfavorable attitudes would likely mean limited levels of collaboration with AI. The downward push on collaboration level could be offset, however, in contexts where AI is mandated. Prior work outside of the AI domain suggests that if an organization wants all of its employees to have some basic competence in a given expertise domain, then using that skill should be required by the company (Bezrukova et al., 2016). According to this line of reasoning, the mandatory use of AI also sends a message about the organization's commitment to AI (Vassileva & Palamarova, 2021). In these instances, employees are expected to interact with the technology, despite their negative attitudes and misgivings (Heidenreich & Talke, 2020). An organization's decision to mandate AI use might reflect ongoing relationships with regulators, competitors, or partners inducing the organization to adopt a technology (Hartwick & Barki, 1994). A team might hold a negative attitude toward AI, yet managers expect the team to engage with the AI.

In line with Tsai and colleagues (2017) and Lapointe and Beaudry (2014), we argue that when teams do not like AI but have little discretion regarding its use, the team will likely comply and engage with AI, perhaps through minimal use. Consider the case above about the chatbot AI that works with a supply chain team and notices a storm coming up. Instead of completely ignoring the weather warning (low collaboration), humans may note and document the warning but not fully engage with AI during alternative evaluations (medium collaboration). When teams have negative attitudes toward AI, mandating AI could also signal organizational commitment and empower teams to explore collaboration opportunities with AI. Research shows how the collective motivation reflected in team empowerment may shape the use of technology (Maruping & Magni, 2015). Mandatory use raises the floor on team collaboration when a team has negative attitudes toward AI. We expect the engagement level to be higher than in the previous condition of negative attitudes and mandatory use, but not as high as in teams with positive attitudes and voluntary use (see Table 1).

Proposition 2. *(P2):* Teams with negative AI attitudes that are mandated to use AI will have medium levels of engagement with AI.

Positive AI Attitudes and Voluntary Use of AI

Research on traditional technologies (e.g., Hwang et al., 2016) suggests that one of the most challenging management tasks is getting users' buy-in by creating positive attitudes toward the adoption of a new system. People with positive attitudes toward AI see the opportunities AI offers and are more likely to engage with it (Lichtenthaler, 2020). Unlike negative attitudes toward AI that may reflect an emotional bond with human interaction (Lichtenthaler, 2020), teams with positive attitudes toward AI are internally motivated (Heidenreich & Talke, 2020) as they would want to adopt the innovation voluntarily. Under this condition, a chatbot AI that works with a supply chain team may take the following form: Chatbot notices a storm coming up that will disrupt shipping times and offers the team alternative routing. The humans in the human–AI team engage in fine-tuning the risk profile and alternatives. Similarly, in the case of a search and rescue team, the human–AI team may develop custom protocols where the "AI-dog" goes into new areas first and provides information to prioritize the search.

The critical association between positive attitudes and discretion over use generalizes beyond these examples. The more employees feel they have discretion over how their work is done, the better the story will be for a teams' motivation and positive psychological well-being (Gagné & Deci, 2005). In such cases, if there is a willingness and desire to use a novel work process or technology by the group, and the group uses the technology on their own volition, then the "sweet spot" of team adoption will be realized. In this case, internal (team attitudes) and external (voluntary AI use) conditions will result in a high level of engagement and collaboration associated with AI (see Table 1).

Proposition 3. *(P3):* Teams with positive AI attitudes that can voluntarily use AI will have the highest levels of engagement with AI.

Positive AI Attitudes and Mandatory Use of AI

Moving away from the sweet spot of Proposition 3, we consider a final condition where a team is inclined to embrace AI but is also mandated to use the technology (see Table 1). Such teams will be likely to rely upon AI to guide their work. But in this case, where the adoption decision does not rest within the team (having low autonomy), this may mean a lower ceiling on engagement with AI than the voluntary, positive attitude condition. Substantial research in job design suggests that mandating use has implications for autonomy and a sense of job control (Deci & Ryan, 2000). Autonomy/job-related discretion is a key factor related to many psychological outcomes (Hackman & Oldham, 1976), including physical and psychological health of employees (Karasek, 1979). Drawing from examples in self-service technology (Feng et al., 2019), when the basic psychological need for autonomy is unmet, there is the potential for loss of motivation, meaning less engagement with AI.

Research shows that when the choice is restricted, teams may engage in adverse behaviors ranging from slow performance, misusing, sabotaging, or oppositional behavior (Ajzen & Madden, 1986; Heidenreich & Talke, 2020; Lapointe & Rivard, 2005; Scholl, 1999). Continuing with our fictitious search and rescue team, in the case of positive team attitudes and mandated use, the humans might like the “dog” but resist the lack of autonomy by chaining it to a fence and ignoring the information it provides about heat signatures and stability of the demolished buildings. Still, we expect a certain degree of engagement with technology in this context (Collier & Barnes, 2015; Meuter et al., 2005; Robertson et al., 2016). In the example above, humans will still travel with the robot and forward partial information they think would help to prioritize the search.

As shown in Table 1, we anticipate that when teams have positive attitudes but AI use is mandatory, the overall level of collaboration will suffer despite the willingness of the group to try AI technology. The mandate will conflict with the teams’ attitudes, leading to tensions (Deci & Ryan, 2000) and process losses. Thus, when AI is viewed positively by the team, the effect of mandatory use has a suppressive effect on collaboration in the team, and the level is not as high as the positive attitudes-voluntary condition.

Proposition 4. *(P4):* Teams with positive AI attitudes where AI use is mandated will have medium levels of engagement with AI.

Discussion

In this conceptual paper, we identified and assessed research across multiple disciplines to synthesize new knowledge about two factors (attitudes and discretion) that may drive human collaboration with AI on the team level. We first reviewed research across groups and teams, information systems, social psychology, engineering, and other areas to guide our theorizing (Patriotta, 2020). Based on the review, we generated a team-level theoretical framework. We explain how a team's collective attitudes toward AI, and whether the AI is introduced voluntarily or mandated, jointly influence the level of collaboration with the AI. Taking a perspective of AI based on collaboration as opposed to automation (National Academies of Sciences, Engineering, and Medicine, 2022), we developed propositions for AI's integration into work teams.

We show that, depending on the team's initial attitudes about AI, mandated AI can have asymmetric effects on collaboration level. When AI is viewed positively by the team, mandated AI suppresses collaboration with the AI. But mandatory use can elevate collaboration with the AI when a team initially has negative attitudes toward AI. We demonstrate how discretion combined with human team member attitudes about AI can produce a variety of responses of which teams and organizations should be aware. Our theory can help organizations leverage AI in teams by providing insights into how AI changes team dynamics and what we can do to support teams to benefit from AI.

While our focus is on the initial stages of how AI is introduced in teams, teasing out what could dial up or down the relationships we propose is also important. For example, adding to some of the factors discussed elsewhere (c.f., Parker & Grote, 2022; Wolf & Stock-Homburg, 2022), prior experience with the task, technology, or team members (Carlson & Zmud, 1999) may also affect the dynamics we describe. Experience offers richness across how teams perceive the situation (and likely alters AI outcomes). Human and AI team members may see new options. Communication can flow more efficiently; the team can tailor behaviors to the tools, task, and actors. Just like humans working in teams, AI and teams benefit from working together on tasks. The team has a greater understanding of where knowledge is held, how information should flow, and how to collaborate given that understanding (e.g., transactive memory, Bachrach et al., 2019; P. Gupta & Woolley, 2021).

As we address the implementations of these technologies for teams, we attempt to match the energy computer science and engineering colleagues apply to the design of AI. While management scholars have paid little attention to AI, especially in teams, there are indications that this is changing (Glikson & Woolley, 2020; Raisch & Krakowski, 2021; Wolf & Stock-Homburg, 2022). Overall, our analysis suggests it is important to understand the joint team-level effects of team attitudes toward AI and discretionary AI use on team collaboration and why these effects are asymmetric. These two constructs have not been brought together at the team level, despite being frequently linked to technology adoption (Heidenreich & Talke, 2020). Our conceptual boundaries also allow our modeling to work across the different manifestations of AI and the different roles AI can play in groups (e.g., embedded, dynamic, autonomous, and understood or not). In the next section, we identify new areas for future efforts (Short, 2009) and consider potential research opportunities. We focus on attitudes and discretion, and also AI and collaboration more broadly.

Frontiers for Future Research

Negative/Positive Team Attitudes. Our primary focus in this paper was to consider team attitudes as inputs affecting human–AI team collaboration. However, important questions remain regarding what leads teams to embrace (collaborate with) AI or not. Team composition may offer fruitful clues on advancing our understanding of what drives team AI collaboration. For example, Charness and colleagues (2018) find that older individuals, conscientious participants, and women have more reservations about driverless cars (a well-known AI application). Other factors, such as culture and previous knowledge or experience with AI (Bartneck et al., 2007), could add to how teams evaluate their AI teammates. We should not neglect temporal dynamics as a feedback loop is possible with prior AI attitudes feeding back into future team attitudes.

Beyond the role of potential moderators and other factors affecting AI, the nature of attitudes themselves is critical. Attitudes are complex, whether related to AI or other people. Individuals' explicit versus implicit evaluations may differ (just as racial biases may be explicitly disavowed, yet still implicitly affect responses, Greenwald et al., 1998). For instance, Fietta and colleagues (2022) show that in word and image sorting tasks, while most participants expressed a positive attitude toward AI, their implicit responses seemed to point in the opposite direction. Moreover, depending on the particular situation or the specific task AI is responsible for, people's attitudes might change (e.g., AI making moral decisions, Bigman & Gray, 2018). For example, AI responsible for downsizing decisions may not be particularly popular in a team, whereas AI helping with paperwork and scheduling might be very popular with the same team. The scope and depth of AI team attitudes seem limitless for future researchers interested in increasing our knowledge of human–AI team collaboration.

AI Discretion: Voluntary versus Mandatory

There are other important considerations in our model and the variables we study. First, the voluntary versus mandatory distinction we pose for discretion is not really dichotomous. Organizations may mandate a technology, offer it to teams to use voluntarily, or something in between (Ram & Jung, 1991). Prior tools for the task may still be available and enable people to work around the "mandated" system (Bader & Kaiser, 2019). Collaborative adjustments to workflow can also provide alternatives to using a mandated process (Mörike et al., 2022). On the other hand, some systems are truly mandated. Envision the case of the technologies running systems of shipping containers. The employees and customers of freight forwarders may not have any choice but to use the mandated tools for booking, quotations, etc. (Balci, 2021).

Employee perceptions of voluntariness suggest another avenue for future research. For example, will infrequent use of AI (either because of the team's task cycle or something else) be associated with more felt voluntariness? Suppose the team sees the AI's purpose as primarily compliance. Will that lead to lower felt voluntariness? If teams focus on innovation as the AI's purpose, will that perception be associated with enhanced felt voluntariness? The group setting itself can make technology like AI seem more voluntary. Boudreau and Robey (2005) described how a group can, working together, get around or overcome constraints imposed by technology. These opportunities supplied by the social environment can include group members taking turns in operating the technology or negotiating the extent of control imposed. Thus, a group context can affect the sense of voluntariness, diminishing the effects associated with a felt loss of control or autonomy.

Discretion can also vary due to team dynamics. Individuals in the group with the most power can direct lower-status individuals to interface with the AI. Since at least some of the group avoids the technology, it makes AI collectively perceived as voluntary. This way, there is more AI-use autonomy within the group, but not all. Traditional technology research has already found similar examples. Physicians ask nurses or other staff to engage with information systems (ISs) rather than having to interact with it themselves (Bhattacherjee & Hikmet, 2007). University administrators direct staff to engage with the IS (Rai et al., 2002). Overall, power differentials make the felt differences in discretion in the group more likely.

Human–AI Collaboration

There are many avenues for improving our understanding of human–AI collaboration. One of these is reconsidering what we mean by a "team." As AI gains agency in organizational practice (e.g., Murray et al., 2021), defining teams as composed of humans only becomes limiting and not reflective of contemporary workplaces. Our literature review shows that definitions of teams are fragmented (e.g., Glikson & Woolley, 2020; Wolf & Stock-Homburg, 2022) and that broader perspectives may have value (Wageman et al., 2012). At the same time, we find only early attention to awareness and mental models of AI (e.g., Bansal et al., 2019).

Related to the definitional issue is the meaning of AI as a teammate. The view of AI as a teammate suggests that there might be potential competitive advantages due to complementary use of human intelligence and AI (Lichtenthaler, 2020). Yet, researchers vary on whether AI can fully function as teammates (Beans, 2018; L. Larson & DeChurch, 2020). Sycara and Sukthankar (2006), for example, noted that AI-only teams differ from human–AI teams but still remain "teams." Although Sycara and Sukthankar suggested that "current software agents lack the dynamism and adaptiveness" (p. 1) needed for human–AI teamwork, AI-only teamwork is possible if coordination and communication are well thought out. It is worth revisiting these boundaries.

Our review and subsequent analysis trigger additional questions. For example, what is the role of subgroups or faultlines within a human–AI team and the attitudes of team members who are not working directly with the AI? To organize these topics, we can apply input-mediator-output-input (IMOI, Ilgen et al., 2005) models from the groups and teams literature. You and Robert (2017) and McNeese and colleagues (2021), for example, consider IMOI perspectives related to intelligent technology and teamwork. Table 2 offers examples of traditional topics and possible AI applications. Such perspectives acknowledge the recursive dynamics of teams working with AI and the possibility of adjustment to attitudes and other factors over time.

In this paper, we considered teams at the meso level. Future research should use the IMOI perspective to add cyclical causal feedback to the consideration of human–AI teams. Additionally, research focused on multilevel dynamics (e.g., Burton-Jones & Gallivan, 2007; Humphrey & LeBreton, 2019; Klein et al., 1999) may deepen our understanding of human–AI team collaboration, though this topic was beyond our scope. Specifically, these dynamics can include inertia, feedback, asymmetric influence, and endogenous change (Cronin & Vancouver, 2019). Considering these aspects of human and technological action on both micro and meso levels (Klein & Kozlowski,

Table 2. IMOI Examples of AI Connections to Traditional Management and Group Constructs.

	Construct	AI Example
Inputs	Interdependence	Kind of interdependence the AI–robot team should adopt
	Faultlines	Faultlines in AI–robot teams
	Roles	Role (and task) differentiation
Mediators	Conflict	Noncompliant AI (or humans) in AI–robot teams
	Shared leadership	Level of control given to the AI in AI–robot teams
	Psychology safety	Trust toward AI in AI–robot teams
Outputs	Team effectiveness	Effectiveness of AI–robot teams

2000) can provide a more realistic view of AI in teams. For example, future research can expand to include AI actors in multilevel examinations of adaptive performance (Han & Williams, 2008).

We can also transform what we have learned from our theory into interesting, meaningful, and potentially actionable knowledge (Post et al., 2020). Clearly, there is a variety of capabilities and roles possible in human–AI teaming (e.g., Figure 3)—all with the potential to help teams be more productive. Managers should strive to keep in mind the current and future power and limitations of AI. For example, if a team of employees use AI to augment the team's decision-making process (Leyer & Schneider, 2021), then team members may be freed from time-consuming tasks by the AI and can direct efforts to other areas. A surgical team may, for instance, find that augmenting decision-making by AI speeds accurate diagnoses. On the other hand, AI that simply automates might remove power from a team accustomed to making decisions through its own processes (e.g., Zuboff, 2019).

Conclusions

While both popular media and the general public have recognized the implications of AI for some time (sprinkled typically with a sense of concern), management research, especially on AI as a member of a group, is still rare. Apart from a few studies considering the role of trust in AI or related issues (e.g., Glikson & Woolley, 2020; L. Larson & DeChurch, 2020; Man Tang et al., 2022; Wolf & Stock-Homburg, 2022), many open questions remain about AI as a player in work teams and what that means for humans in these teams. One paper cannot take on all aspects of AI in teams. We focused on team attitudes about AI and its place as an optional (at the team's discretion) or mandated component of the work process. We find the answer to the question about people collaborating with AI is more nuanced than simply, "will they or won't they?"

We conclude that the level of collaboration is asymmetrically affected by the interaction of attitudes and discretion in using AI. A group positively inclined to AI will have that enthusiasm dampened by being forced to use it. In contrast, a group negatively inclined will see its propensity to collaborate with AI heightened by mandates for AI use. Groups given discretion (voluntary use) see different outcomes, with the resulting collaboration levels at the extremes; positively inclined groups that had a choice and negatively inclined groups that freely declined collaboration.

While there is varied business rationale on why to mandate AI or not, our model is fundamentally about something else. Leaving AI use at the teams' discretion represents the potential for a maximum level of collaboration, where the main driver will be the initial condition of positive attitudes toward AI. As a practical matter, the task of management is then not a decision to mandate or not, but to convince teams that the AI will be a positive addition to their jobs. By comparison, mandated AI, per our asymmetry model, constricts the level of collaboration (medium levels in both cases we consider). We thus offer a new understanding of human–AI group collaboration and emphasize the need for managing team attitudes and discretion strategies, promoting new research directions regarding AI's implications for teamwork.

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Notes

1. https://qz.com/135149/the-first-ever-hashtag-reply-and-retweet-as-twitter-users-invented-them
2. We acknowledge this research given it may be possible to generalize to more intelligent technologies and given some people may not understand AI as different from algorithms more generally.

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