Journal of Organizational Behavior

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Journal of Organizational Behavior

RESEARCH ARTICLE OPEN ACCESS

Is Our Future Colleague Even Human? Advancing Human-AI Teamwork from An Organizational Perspective

How Can Teams Benefit From AI Team Members? Exploring the Effect of Generative AI on Decision-Making Processes and Decision Quality in Team–AI Collaboration

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Received: 1 December 2023 | **Revised:** 18 April 2025 | **Accepted:** 20 May 2025

Funding: This work was supported by Bundesministerium für Digitales und Verkehr (45FGU140_B) and Karin-Islinger Stiftung.

Keywords: AI team member | artificial intelligence | decision-making | generative AI | team–AI collaboration

ABSTRACT

Human teams with distributed knowledge can make high-quality decisions but often fail due to decision-making asymmetries. As AI team members become integrated collaborators, understanding how AI can reduce these decision-making asymmetries is essential. However, little is known about how AI team members can reduce these asymmetries and whether new AI-specific asymmetries emerge from team–AI collaboration. Building on the information asymmetries model, we conducted an exploratory experiment with 215 individuals across 81 teams performing a hidden profile task under three knowledge configurations: (1) human teams with asymmetric knowledge, (2) teams collaborating with AI with centralized knowledge, and (3) teams collaborating with AI with asymmetric knowledge. Our results show that teams with centralized AI knowledge make more accurate decisions than human teams due to reduced decision-making asymmetries, trust in AI, beneficial AI information processing, and a balanced AI collaboration focus. In contrast, teams with asymmetric AI knowledge show only moderate reductions in decision-making asymmetries. Moreover, due to emerging AI-specific asymmetries—such as mistrust, nonbeneficial AI information processing, and a critical AI collaboration focus—these teams fail to outperform human teams. We integrated our findings into process models that illustrate how successful team–AI collaboration depends on effective teamwork between human and AI members.

1 | Introduction

Organizations are integrating generative artificial intelligence (AI) team members to collaborate with humans on increasingly complex decisions (Bankins et al. 2024). AI team members are characterized by their ability to participate in human collaboration processes and their cognitive abilities (McNeese et al. 2018; Seeber et al. 2020). Thus, generative AI systems based on large language models are prime examples of agentic AI team members (Baird and Maruping 2021). They can generate output and provide information, enabling collaboration with humans across a wide range of decision-making tasks (Aydın and Karaarslan 2023). These technological advances are promoting teams collaborating with AI as new organizational decision-making units (Ulfert et al. 2024). Specifically, team–AI collaboration[1] offers significant potential to benefit human teams with *distributed knowledge*, such as multidisciplinary teams in management or medicine, as they are often responsible for making far-reaching and fundamental decisions (Schulz-Hardt and Mojzisch 2012; Sohrab et al. 2015). These teams are expected to make better decisions than each team member alone by achieving synergies through leveraging their distributed knowledge (Lu et al. 2012; Schulz-Hardt and Mojzisch 2012). However, research in the context of hidden profiles has revealed that teams with distributed knowledge often fail to make better decisions due to suboptimal team decision-making processes (Sohrab et al. 2015). The Information Asymmetries Model (IAM) describes hidden profiles as situations where knowledge is distributed asymmetrically, which can lead to suboptimal integration of critical insights during team discussions (Brodbeck et al. 2007). Asymmetric knowledge distribution occurs when individual and collective information points to different decisional alternatives. Thus, teams must counterbalance this asymmetry by effectively integrating distributed information. However, the IAM proposes that teams often fail in this effort due to two key information processing asymmetries at the team level and one at the individual level. The team level asymmetries refer to negotiation focus (reliance on prediscussion preferences) and shared information bias (a tendency to focus discussion on shared rather than unshared information), whereas the individual level asymmetry is social validation (reliance on information that is confirmed by others) (Brodbeck et al. 2007).

However, including a generative AI team member could fundamentally reshape how teams make decisions by introducing new dynamics in how information is processed (Gurkan and Yan 2023). This shift brings both potential benefits and challenges related to the generative AI team member's knowledge and capabilities, which might be deeply interconnected. On the one hand, generative AI team members might help reduce information processing asymmetries within teams, which could, in turn, enhance decision quality. This potential arises from the complementary strengths of human and generative AI team members (Hemmer et al. 2021): Humans contribute contextual understanding and tacit knowledge, whereas generative AI team members offer data-driven insights and advanced information management capabilities (Fügener et al. 2022). For instance, generative AI team members can efficiently retrieve, organize, and synthesize large volumes of information, often at a scale that exceeds human processing capacity (Feuerriegel et al. 2024). When these complementary capabilities are integrated, they can create synergies that lead to improved team performance and decision-making (Hemmer et al. 2021). Building on this, teams with distributed knowledge may benefit from collaborating with generative AI team members, as they could help them overcome challenges in effectively processing and integrating their information (Brodbeck et al. 2007). On the other hand, AI team members can produce incomplete, misleading, or false information, which poses risks to decision quality if not properly processed (Łabuz and Nehring 2024). To fully benefit from team–AI collaboration, human team members must critically assess the contributions of AI team members and integrate them carefully (Fügener et al. 2022; Jussupow et al. 2021). These challenges are further compounded by the "black box" nature of generative AI, which makes it difficult for human team members to fully understand the scope, reliability, or limitations of AI contributions (Łabuz and Nehring 2024).

Together, these potential benefits and challenges highlight a central tension in team–AI collaboration that is currently not sufficiently understood, namely, how team–AI collaboration affects overall team decision-making processes and outcomes (Schmutz et al. 2024; Zercher et al. 2023). Although generative AI team members may reduce information processing asymmetries among human team members, they may also introduce new asymmetries specific to team–AI collaboration. This tension remains poorly understood both theoretically and empirically. From a theoretical perspective, existing theories of human teaming, such as the IAM, have limitations in explaining team decision-making in team–AI collaboration, as they do not account for the unique characteristics introduced by AI team members (Zercher et al. 2023). These include the distinct nature of AI knowledge and the emerging patterns of interaction between human and AI team members, which may be central to understanding how teams can make accurate decisions in team–AI collaboration. From an empirical perspective, human–AI collaboration research has primarily focused on individual humans working with AI, overlooking team–AI collaboration (O'Neill et al. 2022; Schmutz et al. 2024; Zercher et al. 2023). Only a small body of research has examined the teaming processes involved in team–AI collaboration. This limited literature reveals inconsistent findings on whether AI improves or hinders team processes, such as communication, coordination, trust, and team cognition, as well as team performance (Schmutz et al. 2024; Zercher et al. 2023). To address these inconsistencies and the existing research gap, we argue that it is necessary to consider two types of asymmetries: first, the established asymmetries in human team decision-making, as outlined in the original IAM (Brodbeck et al. 2007) and, second, the new asymmetries introduced through collaboration with AI team members, particularly those related to AI knowledge. Accordingly, we focus on the following overarching research question:

RQ: How does the integration of AI team members with varying knowledge affect decision-making processes and outcomes in teams with distributed knowledge?

To address this question, we conducted a preregistered exploratory mixed-method laboratory experiment in which 81 teams had to solve a hidden profile task (Schulz-Hardt et al. 2006) in three different knowledge configurations, that is, the amount and structure of decision-relevant information distributed across the human and AI team members: (1) human teams with asymmetric knowledge, (2) human teams collaborating with AI team members with centralized knowledge, and (3) human teams collaborating with AI team members with asymmetric knowledge. We analyzed quantitative survey responses, qualitative data from videotaped team discussions, and chat protocols from conversations with the AI team member (ChatGPT-based) to understand why some teams arrived at correct team decisions and why others failed. In doing so, we investigated asymmetries in human teams and explored new asymmetries specific to team–AI collaboration.

Our research offers several contributions. First, we contribute to the literature on human–AI collaboration and organizational behavior by exploring how AI impacts team decision-making processes and outcomes (Schmutz et al. 2024; Zercher et al. 2023). Much of the existing literature on human–AI collaboration focuses on how individuals can successfully collaborate with AI (O'Neill et al. 2022), and the small body of literature on team–AI collaboration offers conflicting evidence on the effect of AI team members on teaming processes and outcomes (Zercher et al. 2023). We demonstrate how AI team members can benefit human teams by reducing asymmetries in team decision-making and highlighting how the effectiveness of this reduction is contingent on the AI's knowledge. Second, previous research has often approached the topic of AI as a team member using principles of human teaming (Zercher et al. 2023). However, our understanding of the unique challenges for human teams collaborating with AI team members is still limited. Therefore, we expand the IAM to account for specific asymmetries during collaboration with AI team members and offer more detailed insight into the additional factors to be considered for successful team–AI collaboration. Third, our study contributes to the literature on team–AI collaboration (Ulfert et al. 2024; Zercher et al. 2023) by exploring the underlying human decision-making processes in team–AI collaboration and how they are influenced by the knowledge configuration of the AI team member. Our resulting process models highlight how AI team members can simultaneously cause two conflicting effects on human teams: reducing asymmetries typical of human teams while also requiring teams to address new asymmetries that arise from adequately using and socially processing the information provided by the AI team member, depending on the AI's knowledge configuration. These process models provide a foundation for future confirmatory studies to test the proposed temporal processes. Finally, our study offers practical contributions for organizations seeking to effectively integrate generative AI team members. We provide a nuanced understanding of whether and when teams truly benefit from AI team members, fostering realistic expectations of the potential benefits and challenges for effective team decision-making.

2 | Theoretical Foundation

2.1 | Generative AI as Team Member

AI is currently one of the most transformative technological trends, defined as the "frontier of computational advancements that references human intelligence in addressing ever more complex decision-making problems" (Berente et al. 2021, 1435). AI, such as chatbots and digital assistants (Dennis et al. 2023), typically exhibit superior speed, accuracy, reliability, and scalability compared to humans, complementing human competencies like context awareness and social skills (e.g., Hemmer et al. 2021). Therefore, the goal of deploying AI is often to effectively "team" AI with humans, to achieve synergy in complex, dynamic real-world decisions such as in clinical and strategic decision support, creative idea generation, forecasting, and coordination (Feuerriegel et al. 2024; Han et al. 2024; Jussupow et al. 2021).

The human–AI teaming literature discusses the shift from AI as a tool to AI as a team member (e.g., McNeese et al. 2018). Seeber et al. (2020) define AI team members as technologies that draw inferences from information, derive new insights, provide information, test assumptions, debate the validity of propositions, propose solutions to unstructured problems, and participate in cognitive decision-making. These advanced cognitive and collaborative capabilities align with the capabilities demonstrated by generative AI. Generative AI is a class of AI that can generate new content, such as text (e.g., ChatGPT), images (e.g., DALL-E), or audio, based on their training data (Feuerriegel et al. 2024). Currently, organizations are increasingly deploying generative AI based on large language models, like ChatGPT, that can generate human-like responses to natural language prompts (Aydın and Karaarslan 2023). Thus, they can facilitate collaboration on complex tasks with humans, making them prototypical examples of agentic AI team members (Baird and Maruping 2021).

However, AI team members currently still differ from humans in many aspects. For example, most generative AI systems do not yet have the same contextual understanding, critical thinking, interaction style, or appearance as human team members. Additionally, whether generative AI is perceived as a tool or a team member may also depend on contextual factors, such as its interdependence with human team members and the role it assumes during interactions. Generative AI has the potential to operate as both, as it can flexibly adapt to requirements, ranging from the automation of tasks like text generation or information retrieval to interactive cocreation with humans (Feuerriegel et al. 2024). Further, human responses to AI often differ from those to other humans, for instance, regarding trust development (Georganta and Ulfert 2024; Ulfert et al. 2024), satisfaction with team processes (Dennis et al. 2023), and communication (Schmutz et al. 2024). This indicates that findings from the human teaming literature cannot be readily transferred to AI team members (Zercher et al. 2023). In addition, there are significant challenges associated with generative AI team members. One major issue is the propensity to generate false or misleading information, often referred to as "hallucinations" (Łabuz and Nehring 2024). This occurs because the models generate responses based on patterns in their training data, which can lead to inaccurate information. Hallucinations are particularly problematic because they often appear highly plausible and internally coherent. Additionally, biases in their training data can lead to biased outputs. Thus, differentiating between accurate and inaccurate AI-generated knowledge can be challenging for human team members (Łabuz and Nehring 2024). This is exacerbated by AI's black-box nature, where humans often lack insight into its knowledge or reasoning behind conclusions (Berente et al. 2021). Thus, humans must effectively integrate AI knowledge with their own (Jussupow et al. 2021).

2.2 | From Human Teaming to Team–AI Collaboration

Team–AI collaboration is defined as a "set of two or more humans who interact with an AI dynamically, interdependently, and adaptively toward a common and valued goal/object/mission, and who have each been assigned specific roles or functions to perform" (Zercher et al. 2023, 4). Research in the field of organizational behavior mainly investigates how team processes and team performance are affected by aspects of leadership (e.g., Kelemen et al. 2023) or diverse team composition (e.g., Kearney et al. 2022; Waldman and Sparr 2023). The literature on team composition, however, holds important implications for team–AI collaboration, as it has shown that team composition affects teaming processes such as information elaboration (Kearney et al. 2022), conflict and cohesion (Luksyte et al. 2022), and information exchange (van Knippenberg et al. 2024). Given the inherent differences between humans and AI, integrating AI team members can be seen as a variation in team composition that could affect teaming processes and team performance. This is supported by a recent literature review by Zercher et al. (2023), which summarizes research on the differences in teaming processes and team performance between human teams and teams that collaborate with AI. The review found that research on human–AI collaboration focuses mainly on individuals collaborating with AI, neglecting the complex and specific dynamics of team–AI collaboration (Lyons et al. 2021; O'Neill et al. 2022). The limited empirical studies on team–AI collaboration provide inconclusive evidence regarding whether AI improves teaming processes and team performance. For instance, communication and coordination tend to be less effective in team–AI collaboration than in human teams (Johnson et al. 2021; McNeese et al. 2018; Schmutz et al. 2024; Zercher et al. 2023). Further, there are conflicting findings on whether team cognition and trust are higher in team–AI collaboration than in human teams (Dennis et al. 2023; Georganta and Ulfert 2024; McNeese et al. 2021; Schadd et al. 2022; Schmutz et al. 2024; Zercher et al. 2023). Similarly, the results on team performance differences between team–AI collaboration and human teams are inconsistent (Demir et al. 2018; Schelble et al. 2022; Schmutz et al. 2024). One contributing factor to these mixed findings may also lie in the methodological approaches used, as previous research has primarily focused on static or artificial simulation scenarios, often employing vignette-based or Wizard of Oz approaches (e.g., Gurkan and Yan 2023). As a result, these studies do not involve real-world team interactions or collaboration with actual AI team members. This lack of external validity further limits our understanding of team processes in naturalistic and dynamic settings (Schmutz et al. 2024; Zercher et al. 2023). Furthermore, although certain isolated team processes—such as trust, team cognition, communication, and coordination—have been studied (Schmutz et al. 2024; Zercher et al. 2023), there remains a significant gap in understanding how AI team members influence team decision-making processes and outcomes. This is especially important to understand in teams with distributed knowledge, as these teams are often involved in making important decisions in practice (Schmutz et al. 2024; Schulz-Hardt and Mojzisch 2012).

2.3 | Team Decision-Making Under Distributed Knowledge

Team decisions can be understood as products of decision-relevant information exchanges (DeSanctis and Gallupe 1987). Especially in human teams with distributed knowledge, information sharing and creating a shared understanding are central to successful team decision-making (DeChurch and Marks 2006; Uitdewilligen and Waller 2018). However, human teams often fail to benefit from their distributed knowledge, as the research on hidden profiles demonstrates (Sohrab et al. 2015; Stasser and Titus 1985). A hidden profile is a team decision-making task designed to experimentally create situations in which decision-relevant knowledge is distributed among team members. In this task, human teams are presented with information about several discrete choices they must discuss to select the best option (Sohrab et al. 2015). Typically, there is one best option, but it cannot be identified by individual team members without exchanging information with others (Schulz-Hardt et al. 2006). This is because, in addition to shared information known to all members, each individual also holds unique unshared information. In hidden profiles, shared and unshared information have different decisional implications, and the alternative implied by the unshared information is the correct one (Lu et al. 2012).

The IAM by Brodbeck et al. (2007) theorizes why human teams fail in these contexts. According to the IAM, teams must counterbalance the asymmetric information distribution through symmetric information sharing during their decision-making. However, teams with asymmetric knowledge typically fail to process information symmetrically (Lu et al. 2012). As mentioned above, the IAM identifies negotiation focus and shared information bias as two key team level information processing asymmetries, and social validation as a key individual level asymmetry, which together play a significant role in team decision-making (Brodbeck et al. 2007). These asymmetries highlight areas where AI team members could potentially aid teams in overcoming common human team biases and achieving higher quality decisions. However, the extent to which teams can leverage AI's vast data storage and analytical capabilities might depend on their ability to integrate AI-generated knowledge in their decision-making processes and to collaborate effectively with AI team members (e.g., Fügener et al. 2022; Jussupow et al. 2021; Robertson et al. 2024). In the following, we will describe these asymmetries in detail. Based on the IAM, we will then theorize how the knowledge and information management characteristics of generative AI team members might impact asymmetries during team decision-making.

2.4 | AI'S Influence on Asymmetries During Team Decision-Making

2.4.1 | Negotiation Focus

Negotiation focus describes a discussion style that centers on negotiating preferences for specific options to identify the majority position (e.g., through voting) and is contrasted with information pooling, a strategy in which team members discuss available information (Brodbeck et al. 2007). The negotiation focus results in decisions that are primarily influenced by prediscussion preferences, that is, individuals' preferences before the discussion (Greitemeyer and Schulz-Hardt 2003). In the case of a hidden profile, human team members are predisposed to enter discussions with suboptimal prediscussion preferences based on their distributed knowledge (Stasser and Abele 2020). Further, correspondence of individual prediscussion preferences increases a team's negotiation focus by promoting faster agreement on a decision. Consequently, this reduces the effort required to exchange all information, often leading to decreased discussion intensity (Brodbeck et al. 2007).

Theoretically, a generative AI team member could reduce the focus on negotiation through its ability to provide, evaluate, and draw inferences from information in line with Seeber et al.'s (2020) definition of AI team members. The information management capabilities of AI contrast with those of human teams, who often rely on negotiation as a strategy to manage information overload (Brodbeck et al. 2007; Hemmer et al. 2021). Therefore, AI team members should enhance information elaboration and improve decision quality by encouraging more in-depth discussions and reducing reliance on suboptimal prediscussion preferences. According to the IAM, this should lead to better decisions (Brodbeck et al. 2007). However, the effectiveness of reducing the negotiation focus may depend on the AI's knowledge configuration, as it can influence information elaboration—a critical factor for decision quality, as highlighted in the organizational behavior literature on effective team decision-making (Breugst et al. 2018; Fraidin 2004; Sohrab et al. 2022). In a hidden profile scenario, there are two knowledge configurations in which an AI team member could be part of the interdependent human team's decision-making process (e.g., Stasser and Abele 2020). The first is an AI team member with the full information set that is distributed across the human team members (AI with centralized knowledge); the second is an AI team member that is part of the hidden profile and, therefore, similar to the human team members, has only asymmetric knowledge. If an AI team member with full knowledge participates in the team discussion, it could more effectively mitigate the negotiation focus, as the AI team member can suggest the correct but least preferred option based on its complete information set, as indicated by hidden profile research (Greitemeyer and Schulz-Hardt 2003). Therefore, AI team members with centralized knowledge should disrupt the team's negotiation focus because they challenge the human team members' suboptimal prediscussion preferences (Mojzisch et al. 2010). This could shift the discussion toward information aggregation to evaluate the AI's unexpected suggestion, redirecting the negotiation focus toward reconciling differences between the human preferences and the AI's recommendation. According to the IAM, this should be reflected in a higher level of discussion intensity and decisions less aligned with suboptimal prediscussion preferences, thus leading to better decisions (Brodbeck et al. 2007; Sohrab et al. 2022). In contrast, an AI team member with asymmetric knowledge would suggest a suboptimal option that agrees with the human's prediscussion preferences, which could validate them and, therefore, not disrupt the negotiation focus (e.g., Sohrab et al. 2022). Hence, the AI team member with asymmetric knowledge's suggestions could potentially reinforce existing asymmetries rather than mitigate them. Therefore, we derive the following hypotheses:

Hypothesis 1a. *Teams in both AI knowledge configurations will have a lower negotiation focus than human teams.*

Hypothesis 1b. *A stronger reduction in the negotiation focus will be observed in teams collaborating with AI team members with centralized knowledge than in teams collaborating with AI team members with asymmetric knowledge.*

2.4.2 | Shared Information Bias

The second main asymmetry in the IAM relates to the shared information bias, which suggests that shared information tends to be discussed more than unshared information (Stasser and Titus 1985). This bias consists of two components: the bias toward mentioning shared information and the bias toward repeating shared information (Brodbeck et al. 2007). First, shared information is introduced proportionally more often during the discussion than unshared information. Second, once introduced, shared information is repeated more often during discussion than unshared information (e.g., Larson et al. 1994). Consequently, teams typically decide on options that align with shared information, which decreases decision quality (Lu et al. 2012; Sohrab et al. 2022).

Collaborating with an AI team member might mitigate the shared information bias through generative AI's capability to provide its full (centralized or asymmetric) information, which could facilitate the integration of unshared information. Further, unlike humans, AI team members do not tend to withhold unshared information and are unaffected by the human team members' discussion biases. Bienefeld et al.'s (2023) findings support this by highlighting that information received through an AI team member can increase information sharing in team–AI collaboration. Similarly, Gurkan and Yan (2023) found that AI assistance can increase information sharing. Still, reducing the shared information bias might be stronger for AI team members with centralized versus asymmetric information, as such AI can offer the full information set, including all unshared information, whereas AI with asymmetric knowledge can only provide its unique unshared information. Therefore, teams collaborating with AI team members with asymmetric knowledge have to exchange their unshared information more proactively. Based on this, we derived the following hypotheses:

Hypothesis 2a. *Teams in both AI knowledge configurations will exhibit a lower shared information bias than human teams.*

Hypothesis 2b. *A stronger reduction in the shared information bias will be observed in human teams collaborating with AI team members with centralized knowledge than in teams collaborating with AI team members with asymmetric knowledge.*

2.5 | Emerging Asymmetries During Collaboration With AI Team Members

In the previous section, we applied the IAM (Brodbeck et al. 2007) to develop hypotheses about how the knowledge configuration of AI team members shapes the collaboration between human team members. However, the IAM does not account for collaboration between human and AI team members. Yet this might be critical for understanding how teams collaborating with AI team members can make accurate decisions (e.g., Schmutz et al. 2024; Zercher et al. 2023). To address this gap, we will adopt an exploratory approach. This approach will enable us to investigate new AI-specific asymmetries that fall outside the scope of traditional human teaming frameworks. In doing so, our study aligns with other exploratory research efforts aimed at building foundational understanding in areas where existing models or empirical evidence remain limited (e.g., Gochmann et al. 2022; Wang et al. 2023). Specifically, we will explore emerging asymmetries during collaboration with AI team members by comparing teams working with AI team members that have either centralized or asymmetric knowledge. These new AI-specific asymmetries will be grounded in the IAM to reflect established dimensions of team decision-making. We define these

AI-specific asymmetries as *AI collaboration focus*, *AI information processing*, and *trust in AI rooted in social validation* (the steps of our exploratory analysis will be described in the method section). This approach will allow us to generate theoretically and empirically grounded extensions to the IAM.

2.6 | AI Collaboration Focus

With AI collaboration focus, we refer to how teams engage with the AI team member during the team decision-making process, including the exploration of the use strategies they apply and how intensely they engage with the AI team member and its suggestions. By introducing two AI knowledge configurations, we explore not only how AI knowledge can reduce asymmetries in team decision-making but also how teams adjust their collaboration focus when working with an AI team member depending on the AI's knowledge configuration. This is important because human teams receive different kinds of information and suggestions from the AI team member based on the knowledge configuration it has (Robertson et al. 2024). This information can either be complete with AI team members possessing centralized knowledge or incomplete with AI team members possessing asymmetric knowledge. Having to identify the AI's knowledge configuration simulates many real-world settings where AI knowledge is often not transparent (e.g., Bragazzi and Garbarino 2024). Therefore, teams theoretically need to identify the AI's knowledge configuration and adjust their collaboration focus accordingly to benefit from the AI's knowledge (e.g., Robertson et al. 2024). However, previous research on team–AI collaboration does not provide clear predictions about how the collaboration focus changes, resulting in the research question:

RQ1: Do teams collaborating with AI team members with centralized knowledge apply a different AI collaboration focus than teams collaborating with AI team members with asymmetric knowledge?

2.6.1 | AI Information Processing

With AI information processing, we refer to integrating AI-generated information in the team's decision-making process, which is a central factor in human–AI collaboration literature (Fügener et al. 2022; Jussupow et al. 2021). In our case, this involves the impact of AI knowledge on the accuracy of team decisions, the level of engagement with AI knowledge, and the discussion of AI knowledge. Human teams collaborating with AI team members that provide centralized knowledge could streamline their decision-making process by accepting the full information set. The AI team member's ability to provide comprehensive insights could reduce the need for human team members to engage deeply with the system to make an accurate decision (see also research on manifest profiles, e.g., Mesmer-Magnus and DeChurch 2009). In contrast, human teams working with AI team members that have asymmetric knowledge must treat the AI's knowledge as complementary (e.g., Gurkan and Yan 2023). It could be assumed that this requires more effort to cross-check and integrate the AI's inputs with the team's collective knowledge, as indicated by hidden profile research (Lu et al. 2012). However, asymmetric AI knowledge contains unique AI insights that are necessary to complete the task properly. Centralized AI knowledge does not contain unique AI information and, therefore, only provides a summary of the knowledge distributed across the team members. Therefore, while varying in how much knowledge they contribute and whether the knowledge is available to all human team members, each AI knowledge configuration offers accurate decision-relevant information. Based on this, teams should process AI information differently depending on the AI's knowledge configuration to fully benefit from its knowledge (Brodbeck et al. 2007). However, because previous research on team–AI collaboration does not provide clear predictions on how AI knowledge processing will be affected by the AI's knowledge configuration, we pose the following research question:

RQ2: Do teams collaborating with AI team members with centralized knowledge process AI information differently than teams collaborating with AI team members with asymmetric knowledge?

2.6.2 | Trust in AI Team Members Rooted in Social Validation

According to the IAM, social validation is an individual level process that explains why teams rely more on shared information (Brodbeck et al. 2007; Greitemeyer and Schulz-Hardt 2003), which might also offer an understanding of how (un)shared AI information affects humans. When a human team member contributes shared information to the discussion, other members can confirm its validity. In contrast, unshared items cannot be validated by other team members and might, therefore, be treated with more skepticism (Mojzisch et al. 2010). In the context of different knowledge configurations in team–AI collaboration, this indicates that an AI team member with asymmetric knowledge possesses unique information that cannot be validated by other human team members. In teams collaborating with AI team members with centralized knowledge, the AI has no unique information, as every piece of information is shared with one or all human team members. Therefore, in the context of team–AI collaboration, unshared AI knowledge could amplify skepticism toward the AI team member, as human team members cannot validate it and might perceive it as an error. These differences in the possibility of social validation could affect trust in the AI team member. In human–AI collaboration, trust is critical, as both excessive trust and mistrust can undermine performance. Excessive trust can lead to reliance on false AI suggestions, whereas very low trust can result in correct AI knowledge being overruled (Glikson and Woolley 2020). Considering the multilevel nature of teams, the formation of trust in AI team members among individual human team members might be influenced by whether other human team members socially validate the AI team members (Ulfert et al. 2024). Based on this, we pose the following research question:

RQ3: Do teams trust AI team members with centralized knowledge more than those with asymmetric knowledge?

As we anticipate that different knowledge configurations will differ in their asymmetries during team decision-making, we assume, in line with the IAM model, that these differences will affect the accuracy of team decisions (Brodbeck et al. 2007).

Research Model

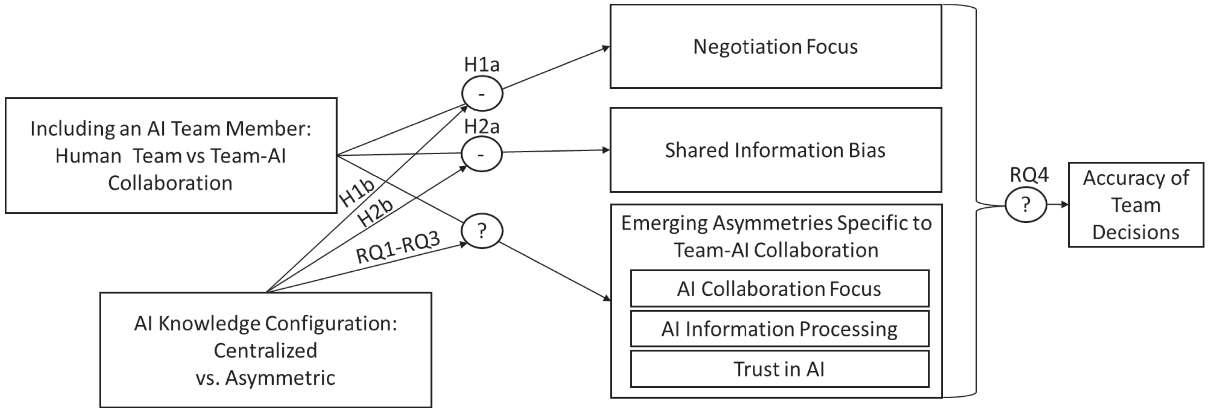

FIGURE 1 | Research model. *Note:* Hypotheses marked with (−) indicate a reduction. Exploratory research questions are marked with (?). The curly bracket indicates that all previous asymmetries contribute to the accuracy.

However, because it is not clear how the AI knowledge configuration will differ in emerging asymmetries in team–AI collaboration, we pose the following exploratory research question:

RQ4: How do knowledge configurations in team–AI collaboration affect team decision accuracy?

All hypotheses and research questions are summarized in our research model, which is illustrated in Figure 1.

3 | Method

3.1 | Study Overview and Participants

We conducted a preregistered (see Appendix E) exploratory laboratory experiment in which small teams were tasked with making a team decision in a hidden profile situation under three different knowledge configurations: (1) human teams with asymmetric knowledge without AI participation (control condition, CG); (2) human teams with asymmetric knowledge collaborating with AI team members that have centralized knowledge (first experimental condition, EG1); and (3) human teams with asymmetric knowledge collaborating with AI team members that have asymmetric knowledge (second experimental condition, EG2). The teams in the CG and EG1 consisted of three people each, whereas the teams in EG2 consisted of two people. This variation in team size allowed us to change the AI's knowledge configuration in relation to the knowledge distribution within the team while keeping the distribution of information consistent across conditions, thus having the same hidden profile task in each condition. We accounted for the difference in team size in the statistical analysis to achieve comparable measures (see Section 3.6). Further, we checked for robustness by ensuring that individual team members' discussion participation and discussion focus on certain options did not differ unduly (see Appendix E).

To gain a comprehensive understanding of team decision-making processes, we employed a mixed-methods approach, integrating both quantitative and qualitative analyses. The quantitative component involved experimentally manipulating the AI team members' knowledge configurations and measuring team decision accuracy and trust in the AI team members through structured surveys and statistical analyses. For the qualitative analysis, we inductively examined video recordings of team discussions and AI interactions via chat protocols, which were based on OpenAI's ChatGPT. We focused on AI-specific interactions, which we later conceptualized as asymmetries using the framework of the IAM. Qualitative and quantitative findings were integrated through three process models that illustrate prototypical team decision-making processes under different knowledge configurations in team–AI collaboration.

Our sample consisted of 223 students, all of whom were at least 18 years old and were fluent speakers of the conversation language (German) used in the experiment. We selected a student sample as they are future professionals and managers who will encounter AI in the workplace. We excluded eight participants due to technical errors of the AI, resulting in a final sample size of $N=215$ on an individual and $N_t=81$ on a team level ($n=75$ and $n_t=25$ in CG, $n=84$ and $n_t=28$ in EG1, and $n=56$ and $n_t=28$ in EG2) collected in two waves (see the Supporting Information). Eleven videos from the team discussions were excluded due to technical issues: two in the CG, three in EG1, and six in EG2. Consequently, the analysis of the team discussion was based on 70 videotaped team discussions. On average, the whole experiment took 60 min. Most participants (65.12%) self-identified as male with a mean age of 23.93 years (SD = 4.03) and were either bachelor (52.56%) or master students (36.74%). All demographic and control variables were equally distributed across the experimental conditions (Appendix D).

3.2 | Procedure

The experiment was conducted in the host institutions' laboratories and was approved by the local ethics committee. The procedure followed the standards for hidden profile studies, adapted from Schulz-Hardt et al. (2006). Participants were informed that they would work together with other human team members in a fictitious airline personnel selection committee to complete a task involving the selection of the best candidate for a pilot position. They were told that each would receive €12 for their participation. Additionally, each participant would receive a bonus of €3 per team member if the team chose the correct candidate. We decided on the incentive of €3 because it balances motivation and conflict in being substantial enough to encourage student participants to actively engage and strive for an accurate decision, while being modest enough to prevent conflict. This balance ensured a cooperative environment focused on accuracy rather than competition. Subsequently, participants were randomly assigned to one of three experimental groups (CG, EG1, or EG2) and to an information profile (X, Y, or Z). Using SoSci-Survey, participants individually completed online questionnaires that included demographic and control variables (see Appendix A for details). Next, they were given 10 min to memorize candidate information, underwent a manipulation check, and indicated their prediscussion preference for a specific candidate. Before starting the team discussion, we informed participants that only a part of their information profile was shared and that each participant possessed some unique unshared information. Additionally, they got the information that there is one optimal candidate. In EG1 and EG2, participants received additional information about the chatbot Alex as the AI team member and how to use it. Then, the team discussion took place verbally in a face-to-face format, with participants seated in a semicircle according to a predetermined plan. Each team had a maximum of 30 min for discussion and was instructed not to use any additional tools. In EG1 and EG2, the AI team member Alex, opened in a laptop browser, facilitated collaboration with the AI via chat. After the discussion, participants completed surveys on the team's decision and their trust in the AI team member on their laptops.

3.3 | Hidden Profile Task

We adapted and pretested the material for the hidden profile task from Schulz-Hardt et al. (2006). The decision task deals with an airline company looking for a new pilot for long-distance flights. The participants played the role of members of the airline company's personnel selection committee. We selected this task because it is highly specific and participants are likely not to have experience in this field. This ensured that they would base their team decision on the information given to them in the experiment. Participants were informed that they would receive reliable information profiles of four candidates (Alpha, Beta, Gamma, and Delta). Further, each participant received one of three information profiles (X, Y, or Z). Each information profile included six attributes per candidate that were either positive or negative and shared or unshared. The total information set consisted of 40 attributes including 10 attributes for each candidate. Shared information consisted of 16 attributes and included the positive attributes of the suboptimal candidates (Alpha, Beta, and Delta), the negative attributes of the optimal candidate Gamma, and one positive attribute of Gamma. Unshared information consisted of 24 attributes and included the other positive attributes of Gamma, as well as the negative attributes of the suboptimal candidates Alpha, Beta, and Delta. Table S2 gives the information distribution about the four candidates across the information profiles.

Through pretesting, we ensured that the four candidates had attributes of similar average strength and valence (see the Supporting Information and Appendix B for more details). The number of positive and negative attributes per candidate, as in "The candidate can concentrate very well over long periods" (positive) and "The candidate is said to be a know-all" (negative), was the decision criterion for identifying the best candidate. Based on this criterion, Gamma, who had seven positive and three negative attributes, emerged as the best candidate because the other candidates had six negative and only four positive attributes. Therefore, most team members were expected to prefer candidates Alpha, Beta, or Delta prior to discussion, indicating a weak hidden profile. We opted for a weak hidden profile as it allows variation in the prediscussion preferences of the participants.

3.4 | Team Discussion Coding

To analyze the team discussion and information exchange in hidden profile settings, we adopted the hidden profile coding scheme developed by Thürmer et al. (2018). We distinguished mentioned from repeated information by coding which team participants (with the information set X, Y, or Z) introduced or repeated specific attributes (Thürmer et al. 2018). Further, in EG1 and EG2, we determined whether attributes were mentioned or repeated before or after the AI usage to investigate the AI's impact on team discussion. Two trained research assistants independently coded 10 randomly selected videos in an iterative process until they achieved a high level of agreement, ensuring the objectivity of the coding (Krippendorff's alpha, $\alpha = 0.91$). After ensuring that the values for interrater reliability, according to Cohen (1988), indicated very good agreement, two trained research assistants applied the coding scheme to all discussions (approximately 22.5 h).

3.5 | Experimental Groups: AI Knowledge Configurations of Chatbot Alex

We implemented a browser-based chatbot named Alex using OpenAI's application programming interface (API) for chat completion via Python's Flask library. The chatbot was designed to utilize the natural language processing engine GPT-3.5-turbo-0301, which is based on OpenAI's large language model GPT-3.5, the most recently released version at the time. Predefined text inputs were used as context (see the Supporting Information). The text inputs in both AI knowledge configurations included instructions on how the chatbot should behave. These instructions covered the conversation language (German and gender-neutral), information about the task, and the decision criterion (ratio of positive to negative attributes) and indicated the equal importance of all attributes. Additionally, we fine-tuned the API parameter temperature to 0.1 to ensure that the AI team member would respond appropriately to the decision context (see Appendix C).

We manipulated the AI's knowledge configuration by varying the candidate information in the automatic text inputs. These text inputs were developed through an iterative process involving several rounds of prompt engineering and testing based on the chatbot's responses. We adjusted the context until two key requirements were met: The AI team member had to provide the correct information set and suggest a specific candidate. The textual inputs (context) were not displayed on the user interface. This effectively concealed the underlying code and settings. Participants were informed that the AI team member possessed decision-relevant information but the AI's knowledge configuration was not disclosed. The AI team member initiated the conversation with a greeting message, stating that it could assist in decision-making and that it was happy to help. Thus, the AI team member was presented as an integral part of the decision-making process, specifically tasked with assisting the team in selecting the best candidate. Alex was explicitly introduced as a "part of the team," rather than merely a supportive tool (see Appendix C). Additionally, the AI team member was given the human name Alex to further highlight its role as a collaborative partner. In EG1, where the AI team member had centralized knowledge, the bot received comprehensive information about all candidates. Consequently, the AI team member could make fully informed decisions and suggest the correct candidate, Gamma. In EG2, where the AI team member had asymmetric knowledge, the bot received only information Profile *Z*. This meant the AI team member could make only partially informed decisions, suggesting an incorrect candidate (Alpha, Beta, or Delta).

3.6 | Measures

3.6.1 | Negotiation Focus

3.6.1.1 | Prediscussion Preferences. We asked the question: "In your personal opinion, which candidate is best suited for the pilot position?" The answer alternatives were the four candidates. To examine how prediscussion preferences affect final team decisions, we coded the team level correspondence of participants' prediscussion preferences with the final team decision from 1 = *very low* to 4 = *very high*. Four would indicate that two participants had a prediscussion preference for the candidate selected by the team. Three would mean that one participant had a prediscussion preference for the candidate that the final team decision selected. Two would mean that no participant had a prediscussion preference for the candidate chosen in the team decision. Lastly, a one would mean that two participants had both preferred another candidate before the discussion.

3.6.1.2 | Discussion Intensity. We summed up all the mentioned and repeated information across teams. These sums were normalized to the number of videotaped team discussions ($n_t = 23$ in CG, $n_t = 25$ in EG1, and $n_t = 22$ in EG2) and human team members (three in EG1 and CG and two in EG2) to obtain comparable measures of the team level discussion intensity across conditions. In EG1 and EG2, the measures of discussion intensity were additionally calculated before and after the AI team member was included in the team discussion. We report the normalized value at the team level for easier interpretability (Appendix F).

3.6.2 | Shared Information Bias

The shared information bias was calculated on the team level based on the completeness of mentioning shared and unshared information and the average repetition rates of shared and unshared information (Thürmer et al. 2018). The completeness of mentioning shared information was calculated as the proportion of shared information mentioned out of all shared information, whereas the completeness of mentioning unshared information was calculated as the proportion of unshared information mentioned out of all unshared information. Values can range from 0% = *no information mentioned* to 100% = *all shared/unshared information mentioned*. The repetition rate of shared information was calculated as the sum of all repeated shared information averaged by the number of shared information. The repetition rate of unshared information was calculated as the sum of all repeated unshared information averaged by the number of unshared information.

The bias toward mentioning shared information was calculated on the team level as the proportion of the completeness of mentioning shared information divided by the sum of the completeness of mentioning shared and unshared information. Similarly, the bias toward repeating shared information was calculated by dividing the repetition rate of shared information by the sum of the repetition rates of shared and unshared information. Values of 50% represent an unbiased discussion, values closer to 100% represent a discussion biased toward shared information, and values closer to 0% represent a discussion biased toward unshared information (Appendix F).

3.6.3 | AI Collaboration Focus

3.6.3.1 | AI Collaboration Strategy. We used an inductive and iterative process to code the different strategies teams applied during their collaboration with the AI team member. Two independent coders (one author and one research assistant) reviewed the videos to identify key AI usage themes through thematic coding. Afterwards, they compared their coding and refined the categories (see Table 1). Another author reviewed the second version of the coding scheme and refined the category descriptions. After ensuring a high interrater reliability (Krippendorff's alpha, $\alpha = 0.77$), all videos were coded by one of the coders involved in developing the coding scheme. The codes in each category were normalized to the number of video-taped team discussions in EG1 ($n_t = 25$) and EG2 ($n_t = 22$) and the number of humans to obtain comparable team level measures.

3.6.3.2 | Acceptance of the AI Advice. The acceptance rate, a team level variable, was operationalized as a dummy variable indicating whether the team's decision corresponded with the AI's recommendation (1 = *advice accepted*, and 0 = *advice disregarded*).

3.6.3.3 | AI Collaboration Intensity. AI collaboration intensity is a team level variable. We assessed how often the team had prompted the AI team member based on the chat protocols.

3.6.4 | AI Information Processing

3.6.4.1 | AI Full Information Set Given. We created a dummy variable from the chat protocols to indicate if teams

TABLE 1 | Descriptive statistics of the AI collaboration strategy.

Strategy	Definition	Quote	EG1		EG2	
			M	SD	M	SD
Weighting$_N$	Assessing the importance, relevance, and valence of specific attributes for the pilot position.	"Should we ask Alex how important it is to take part in training as a pilot?"	1.00	0.82	1.02	0.72
Seeking advice$_N$	Request of suggestions for a particular candidate	"I will ask the AI which candidate it would suggest."	0.32	0.37	0.93	0.95
Questioning AI$_N$	Scrutinizing the AI's responses	"I'm not sure if this is correct."	0.35	0.58	0.90	0.98
Explanation$_P$	Seeking clarification for a specific response	"Let us ask him why he suggested Gamma."	0.13	0.29	0.17	0.29
Aggregation$_P$	Requesting candidate attributes	"Should we ask him what information he has about the candidates?"	0.60	0.41	0.88	1.01
Giving AI attributes$_P$	Assigning specific attributes to the AI	"We should tell Alex the attributes that we can remember."	0.13	0.37	0.36	0.55

Note: Strategies with $_N$ refer to strategies related to negotiation, and strategies with $_P$ refer to strategies related to pooling.

received the full information set from the AI team member (1 = *yes*, and 0 = *no*).

3.6.4.2 | Repetition of AI Information. Based on the chat protocols, we counted how often the AI team member had to repeat the candidate information in its messages and normalized this count to the number of videotaped team discussions to obtain comparable team level measures.

3.6.4.3 | Discussion of Unshared AI Information. We compared the discussion intensity of unshared information from Profile *Z*, which is equivalent to the unshared AI knowledge in EG2, both across and within EG2. To achieve comparable measures across conditions, the discussion intensity of unshared AI knowledge was normalized to the number of videotaped team discussions and human team members to obtain comparable team level measures.

3.6.5 | Trust in the AI Team Member

Trust in the AI team member was examined at the individual level with the inventory by Benbasat and Wang (2005), which contains 11 items distributed across three subscales of competence, integrity, and benevolence on a 5-point Likert scale from 1 = *disagree* to 5 = *agree*. Competence had five items (e.g., "AI Alex was like a real expert in assessing the candidates," $\alpha = 0.80$), integrity three items (e.g., "AI Alex was honest," $\alpha = 0.79$), and benevolence three items (e.g., "AI Alex puts my interests first," $\alpha = 0.67$). The items were adjusted to fit the team decision-making context in this study (overall scale $\alpha = 0.81$).

3.6.6 | Accuracy

Decision accuracy was binary-coded to determine whether each team had chosen the correct candidate.

3.6.7 | Control Variables

To control for individual factors, we assessed each human team members' general disposition to trust humans with a three-item Likert scale ($\alpha = 0.73$) and the disposition to trust the AI team member with three items ($\alpha = 0.74$) adapted from Gefen (2000). The scales ranged from 1 = *strongly disagree* to 5 = *strongly agree* (e.g., "In general, I have confidence in AI/mankind"). Further, we measured participants' prior experience with AI ("I am experienced in the use of AI"), working in teams ("I am experienced in teamwork"), and chatbots ("I am experienced in the use of chatbots") on a 5-point Likert scale from 1 = *strongly disagree* to 5 = *strongly agree*.

3.6.8 | Manipulation Check and Control for AI Behavior

To ensure that participants were attentive during the memorization period and that all candidates were remembered equally, we used attribute recall as a manipulation check (Schulz-Hardt et al. 2006). Each participant received a recall questionnaire in which they were asked to recall as many attributes about each candidate as they could. Participants' ability to remember candidate information did not differ across the different knowledge configurations, and all candidates were remembered equally (for values, see Appendix D). Additionally, we checked whether the AI team member behaved as intended by evaluating the chat protocols based on three criteria: First, the AI team member responded to prompts; second, the AI team member provided its full information set if asked; third, the AI team member in EG1 had suggested Gamma and in EG2 had suggested a suboptimal alternative. We ensured that every team member could see the chat with Alex by asking "Were you able to see the chat history with the AI Alex during the entire discussion?" on a 5-point Likert scale from 1 = *strongly disagree* to 5 = *strongly agree* (for additional controls see Appendix A).

4 | Results

The data were analyzed using SPSS Version 29.0.0.0 (IBM Corp.). We used the Shapiro–Wilk test and the Levene test for homogeneity of variances to check that the requirements for parametric tests were met (see Appendix E). As most of the variables did not meet these assumptions, we based our analysis on nonparametric tests, using the χ^2 test for categorical data, Kruskal–Wallis tests to compare all three conditions, and a Mann–Whitney U test to compare the AI conditions.

4.1 | AI'S Influence on Asymmetries During Team Decision-Making

In the following, we present the results concerning the effect of knowledge configurations on negotiation focus and shared information bias (Hypotheses 1a, 1b, 2a, and 2b).

4.1.1 | Negotiation Focus

In Hypothesis 1a, we hypothesized that teams in both AI knowledge configurations would have a lower negotiation focus than human teams, as measured through prediscussion preferences and discussion intensity. In Hypothesis 1b, we further hypothesized that this reduction in negotiation focus would be stronger in teams collaborating with AI team members with centralized knowledge compared to teams collaborating with AI team members with asymmetric knowledge.

4.1.1.1 | Effect of Prediscussion Preferences on the Team Decision. Almost all teams in the CG decided on a candidate for whom the prediscussion correspondence was very high (56.0%) or high (36.0%), indicating a strong relationship between prediscussion preferences and the final team decision. In EG1, most teams decided on a candidate with very low prediscussion correspondence (35.71%), indicating that the centralized AI knowledge weakened the effect of prediscussion preferences on the final team decision (Hypothesis 1b). EG2 shows a similar pattern as in the CG in that most teams decided on an alternative that at least one (67.86%) or two (17.85%) of the two team members preferred, indicating a strong influence of prediscussion preferences on the final team decision (Hypothesis 1b). A Kruskal–Wallis test confirmed that the effect differed between the conditions ($H[2]=9.08$, $p=0.01$, $r=0.40$). A post hoc analysis revealed that the effect of prediscussion preferences on the final team decision is significantly lower in EG1 than in the CG ($p=0.01$), but there were no further significant differences (see Figure G2a). The heatmaps in Figure 2a–c display the correspondence between team decisions and prediscussion preferences, illustrating different patterns in how certain prediscussion preferences are connected to the final team decisions. Specifically, they indicate a relationship between prediscussion preferences for Gamma and the final team decisions in CG and EG2. To better understand the emergence of correct decisions in EG2 and the CG, and to account for the fact that the measure of the correspondence of prediscussion preferences is influenced by team size, we analyzed the prediscussion preferences for Gamma and their correspondence to the team decisions for Gamma in more detail. We found that 85.70% ($n_t=6$) of the teams in the CG and 100% ($n_t=8$) of the teams in EG2 that made accurate team decisions had at least one team member with a prediscussion preference for Gamma. Correct decisions in CG ($\chi^2[1]=6.87$, $p=0.009$, $\varphi=0.52$) and EG2 ($\chi^2[1]=17.31$, $p<0.001$, $\varphi=0.79$) were significantly related to prediscussion preferences for Gamma. This is not the case in EG1 ($\chi^2[1]=0.49$, $p=0.48$), showing that the reliance on prediscussion preferences is mitigated in EG1, indicating a higher negotiation focus in CG and EG2, supporting our Hypothesis 1b.

4.1.1.2 | Discussion Intensity. To further test our hypotheses on negotiation focus (Hypotheses 1a and 1b), we compared the discussion intensity across the knowledge configurations, as illustrated in Figure 3a. The overall discussion intensity was highest in EG2 (M = 0.78, SD = 0.42), followed by EG1 (M = 0.52, SD = 0.21), with the lowest discussion intensity in CG (M = 0.38, SD = 0.22). These differences were statistically significant ($H[2]=27.86$, $p<0.001$). A post hoc analysis showed that EG2 discussed significantly more information than EG1 ($r=0.29$) and CG ($r=0.59$). Additionally, EG1 discussed significantly more information than CG ($r=0.30$), further supporting the hypothesized lower negotiation focus in EG1 and a high negotiation focus in CG. Interestingly, this result emphasizes that teams in EG2, despite relying on prediscussion preferences for the final team decision, still engaged in intense discussion. This would not be observed if the team relied mainly on voting

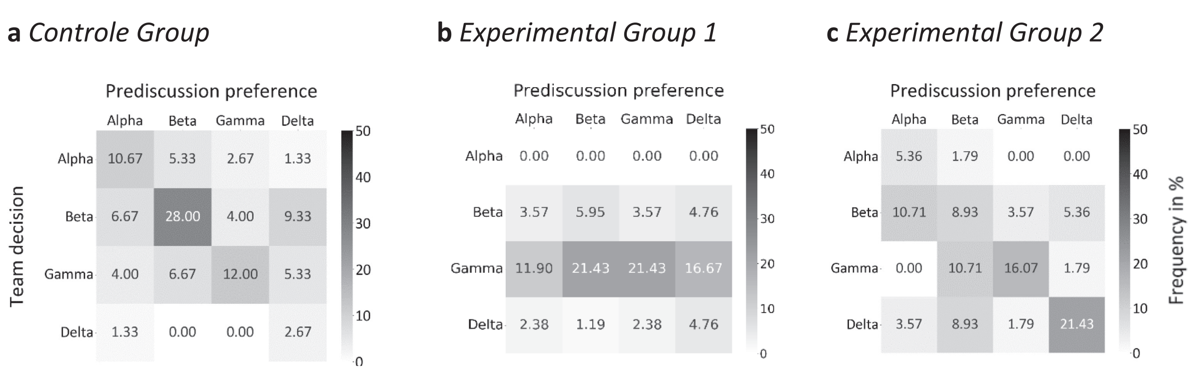

FIGURE 2 | Heatmaps illustrating the relationship between prediscussion preferences and team decisions. (a) Controle group, (b) Experimental Group 1, and (c) Experimental Group 2.

for preferences, indicating a partly reduced negotiation focus in line with Hypotheses 1a and 1b. In both EG1 ($Z=4.84$, $p<0.001$, $r=0.77$) and EG2 ($Z=5.51$, $p<0.001$, $r=0.87$), we observed a significant increase in discussion intensity after the utilization of the AI team member.

In summary, the results support Hypothesis 1a: Teams in both EG1 and EG2 showed greater discussion intensity than the CG. However, only EG1 teams deviated from prediscussion preferences in their final decisions, supporting Hypothesis 1b.

4.1.2 | Shared Information Bias

In Hypothesis 2a, we hypothesized that teams in both AI knowledge configurations would exhibit a lower shared information bias than human teams. In Hypothesis 2b, we further hypothesized that this reduction in shared information bias would be stronger in teams collaborating with AI team members with centralized knowledge compared to teams collaborating with AI team members with asymmetric knowledge. Comparing the discussion of shared information, we found that EG2 (M = 86.08%, SD = 14.05%, $r=0.52$) mentioned the most shared information, followed by EG1 (M = 81.50%, SD = 17.08%, $r=0.45$), whereas the CG mentioned the least shared information (M = 57.61%, SD = 20.36%). This difference was statistically significant ($H[2]=30.46$, $p=0.001$). Similarly, most shared information was repeated by EG2 (M = 0.49, SD = 0.27), followed by EG1 (M = 0.29, SD = 0.20), and the CG (M = 0.29, SD = 0.16). These differences were significant ($H[2]=8.11$, $p=0.017$), with EG2 repeating more shared information than EG1 ($r=0.45$) and CG ($r=0.42$).

Exploring the discussion of unshared information, we found that teams in EG1 (M = 78.67%, SD = 15.78%, $r=0.66$) and EG2 (M = 57.58%, SD = 22.87%, $r=0.73$) mentioned significantly more unshared information than teams in CG (M = 38.95%, SD = 16.89%; $H[2]=31.14$, $p<0.001$). Similarly, the most unshared information was repeated in EG2 (M = 0.72, SD = 0.61), followed by EG1 (M = 0.65, SD = 0.25), and CG (M = 0.55, SD = 0.44), with EG2 having repeated significantly more unshared information than CG ($Z=-14.08$, $p=0.02$, $r=0.33$).

The bias toward mentioning shared information was lowest in EG1 (50.88%), whereas EG2 (59.92%) showed a similar bias toward mentioning shared information as CG (59.66%). Yet the bias toward repeating shared information showed a slightly different pattern. It was still the lowest in EG1 (57.24%) and highest in CG (61.45%). However, the bias toward repeating shared information in EG2 (57.95%) was at a similar level as in EG1. Thus, consistent with Hypothesis 2a, human teams showed the highest shared information bias, whereas, in line with Hypothesis 2b, the AI team member with centralized knowledge was most effective in reducing it (see Figure 4a).

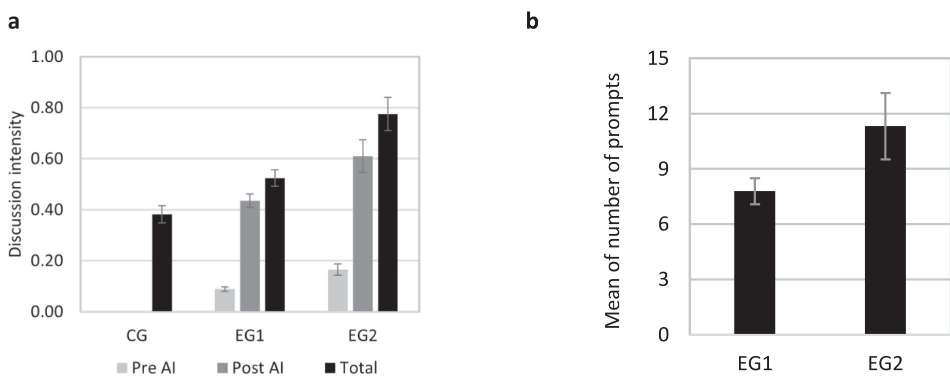

FIGURE 3 | Discussion intensity for each condition (a) and AI collaboration intensity (b). Abbreviations: CG, control group; EG1, Experimental Group 1; EG2, Experimental Group 2.

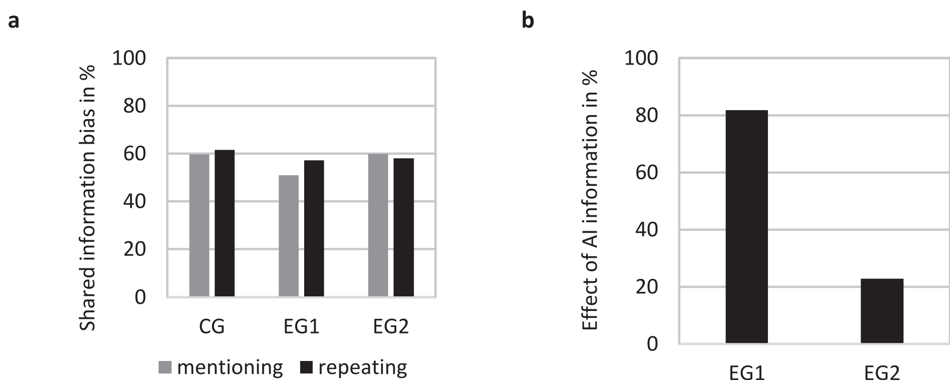

FIGURE 4 | Shared information bias (a) and effect of AI information (b). Abbreviations: CG, control group; EG1, Experimental Group 1; EG2, Experimental Group 2.

4.2 | Emerging Asymmetries During Collaboration With AI Team Members

The following sections will detail our findings on the exploratory research questions regarding emerging asymmetries specific to team–AI collaboration.

4.2.1 | AI Collaboration Focus

RQ1 asks whether teams collaborating with AI team members with centralized knowledge differ in their AI collaboration focus from teams with AI team members with asymmetric knowledge.

4.2.1.1 | AI Collaboration Strategy. Based on the IAM, we categorized AI collaboration strategies into information negotiation (seeking advice, weighting information, and questioning AI) and pooling (information aggregation, seeking explanation, and giving information to AI) (see Table 1). EG1 and EG2 exhibited similarities, with "weighting" having emerged as the predominant method of AI use, whereas "explanation" consistently ranked as the least utilized AI category. However, compared to EG1, EG2 demonstrated a significantly higher mean for the categories "questioning AI" ($U = 360$, $Z = 2.27$, $p = 0.023$, $r = 0.33$) and "seeking advice" ($U = 376.5$, $p = 0.009$, $r = 0.38$). This indicates that the negotiation focus during team decision-making is also reflected in the use of AI in EG2, where teams prioritized gaining an understanding of the AI's suggestions. Interestingly, EG2 also engaged in a more critical collaboration by expressing doubts about the AI's output (questioning AI).

4.2.1.2 | Acceptance of AI Advice. Teams in EG1 were significantly more likely to accept the AI's recommendation (79.19%, $n_t = 19$) than teams in EG2 (40.90%, $n_t = 9$; $\chi^2[1] = 7.05$, $p = 0.008$, $\varphi = 0.39$). Specifically, when combined with the findings on prediscussion preferences, we observed an inverted relationship. Teams in EG1 did not rely on prediscussion preferences for their final team decision; rather, they accepted the AI's suggestions. In contrast, 85.71% of the teams in EG2 decided on a candidate in line with their prediscussion preferences and tended to reject the AI suggestions more often than EG1, indicating that humans tended to treat human preferences and AI suggestions differently depending on the knowledge configuration of the AI.

4.2.1.3 | AI Collaboration Intensity. Teams in EG2 (M = 11.32, SD = 9.51) collaborated with the AI notably more intensely than teams in EG1 (M = 7.79, SD = 3.68) (Figure 3b). Despite a moderate effect size, the difference did not reach the conventional level of statistical significance in the nonparametric test ($U = 288$, $Z = -1.71$, $p = 0.087$, $r = 0.23$).

In response to RQ1, we found that teams adjusted their collaboration focus based on whether they were collaborating with AI team members with centralized or asymmetric knowledge.

4.2.2 | AI Information Processing

RQ2 asks whether teams working with AI members with centralized knowledge process AI information differently than those working with AI members with asymmetric knowledge.

4.2.2.1 | AI Full Information Set Given. We found that in EG1, 81.82% of the teams ($n_t = 18$) who received the AI's full information set decided on the correct candidate ($\chi^2[1] = 9.18$, $p = 0.002$, $\varphi = 0.572$). Conversely, in EG2, only 22.73% of the teams ($n_t = 5$) selected the correct candidate when the AI team member provided its complete information set ($\chi^2[1] = 1.72$, $p = 0.19$, $\varphi = -0.25$). This indicates that only teams in EG1 benefited from the AI team member providing its information, whereas in EG2, there was no relationship between the AI's input and accuracy, suggesting that these teams did not incorporate AI information in a way that improved their decisions (see Figure 4b).

4.2.2.2 | Repetition of AI Information. The AI team member had to repeat its information more often in EG2 (M = 2.22, SD = 0.38) than in EG1 (M = 1.42, SD = 0.15) ($U = 8.00$, $Z = -6.56$, $p < 0.001$, $r = 0.83$). Interestingly, this indicates that although AI information was not associated with better team decisions in EG2, these teams still requested AI information more often than teams in EG1, suggesting that teams in EG2 still actively sought and engaged with AI information.

4.2.2.3 | Discussion of Unshared AI Information. The intense engagement with AI information was also reflected in the team discussion of unshared AI information. Results of a Kruskal–Wallis test revealed that unshared AI information (Profile Z) was more intensely discussed in EG2 (M = 1.01, SD = 0.42) compared to the CG (M = 0.34, SD = 0.26, $p < 0.001$, $r = 0.85$) and EG1 (M = 0.45, SD = 0.14, $p = 0.003$, $r = 0.53$; $H[2] = 11.77$, $p = 0.003$). Moreover, unshared AI information was also more intensely discussed within EG2 (M = 1.01, SD = 0.42) compared to unshared information in the other profiles, Y (M = 0.58, SD = 0.21) and X (M = 0.36, SD = 0.18) ($H[2] = 9.60$, $p = 0.008$, $r = 0.63$). Only the comparison between Profiles Z and X reached the conventional level of significance. Notably, parametric and nonparametric tests yielded differing conclusions: The post hoc Tukey test indicated differences for X and Y (X vs. Z: $p < 0.001$, 95% CI [0.29, 1.02]; Y vs. Z: $p = 0.02$, 95% CI [0.07, 0.80]).

With respect to RQ2, teams' AI information processing varies based on the AI knowledge.

4.3 | Trust in AI Team Members Rooted in Social Validation

Answering RQ3, we found that trust in the AI team member was significantly lower in EG2 (M = 3.21, SD = 0.61) than in EG1 (M = 3.47, SD = 0.58) ($U = 1696.50$, $Z = -2.70$, $p = 0.007$).

4.4 | Accuracy of Team Decisions

The highest accuracy rate was observed in EG1, where 67.85% ($n_t = 19$) of the teams selected the correct candidate. In contrast, EG2 had an accuracy rate of 28.60% ($n_t = 8$), and the CG achieved only 28.00% ($n_t = 7$)—which is roughly equivalent to the guessing probability. Teams in EG1 were significantly more likely to select the correct candidate compared to those in EG2 and CG, $\chi^2(2) = 11.77$, $p = 0.003$, $\varphi = 0.38$. The effect size ($\varphi = 0.38$) suggests a medium to large effect. However, no significant accuracy difference was found between EG2 and CG (see Appendix G for illustration).

Answering RQ4, we found that teams in EG1 achieved significantly higher decision accuracy than those in both EG2 and CG, while no significant difference was observed between EG2 and CG.

4.4.1 | Explaining Differences Between Knowledge Configurations Through a Process Perspective

To explain the complex differences between CG, EG1, and EG2, we developed process models that visualize how the observed asymmetries influence the accuracy of team decisions (see Figure 5). These models illustrate the proposed sequence of events. In the CG, low accuracy resulted from two main team level asymmetries: negotiation focus and shared information bias. Only human teams that overcame these asymmetries or those with prediscussion preferences for Gamma could arrive at a correct team decision. In the AI conditions, we accounted for newly emerging asymmetries resulting from team–AI collaboration and how they manifested depending on the AI team member's knowledge configuration. Here, we theorize that lower levels of trust in AI team members within EG2 serve as a central explanatory factor for several differences between EG1 and EG2. Teams in EG2 collaborated more intensely with the AI team member and engaged more deeply with AI-generated information. However, despite engaging more with AI team members, teams often rejected their advice, questioned their output, and saw no improvement in decision accuracy. This indicates that teams in EG2 failed to identify the correct candidate by combining the AI team member's knowledge with their own. It also suggests they not only rejected the AI team member's advice but relied less on its knowledge overall. The analysis of the videos revealed that the lack of social validation for unshared AI information might have led to a closer scrutiny of the overall validity of the AI's information. Therefore, we summarize the collaboration focus in EG2 as critical and the AI information processing as not beneficial. Thus, teams in EG2 relied on prediscussion preferences for their team decisions. In contrast, teams in EG1 showed a more balanced collaboration focus and beneficial AI information processing.

5 | Discussion

As organizations increasingly implement generative AI team members, many questions arise about how these systems can successfully collaborate with human teams. Extant research on the underlying mechanisms of successful team–AI

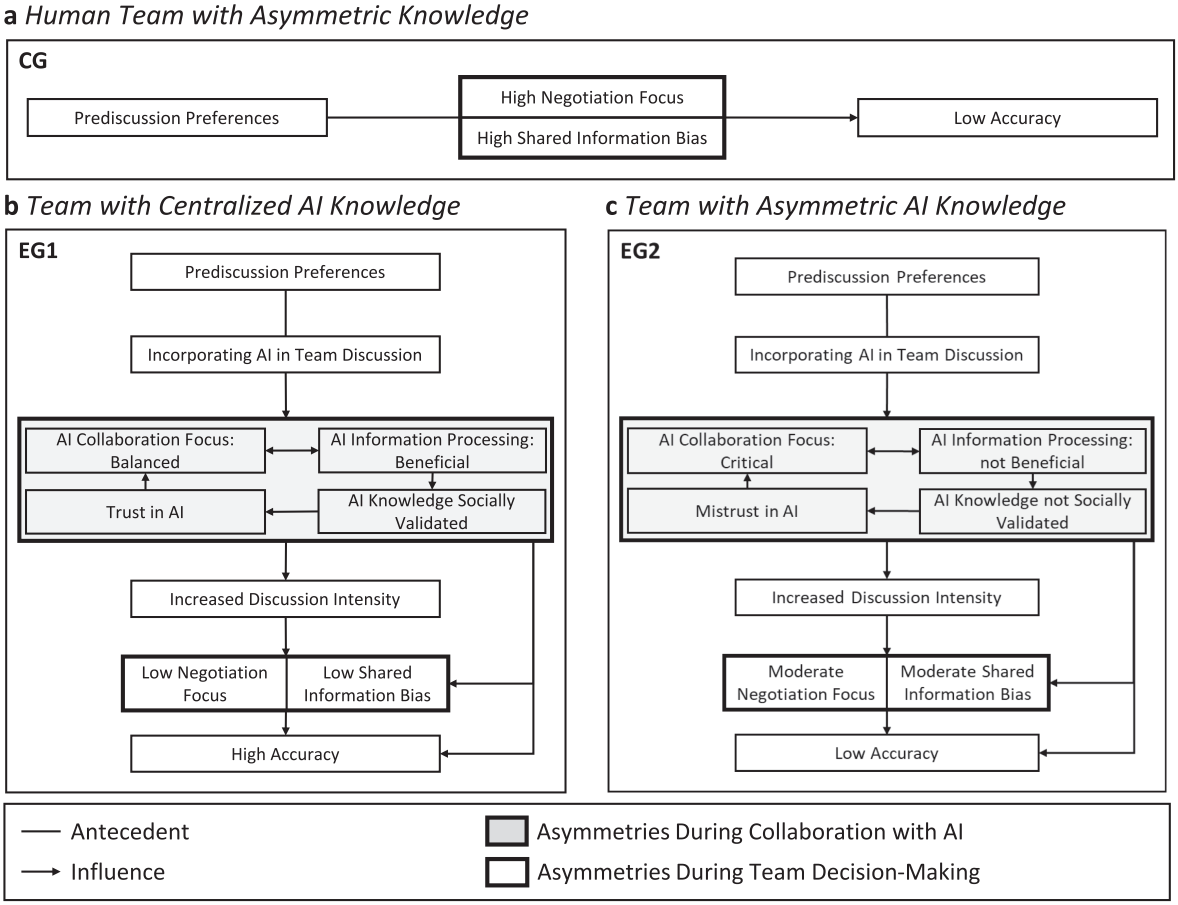

FIGURE 5 | Prototypical decision-making processes in the different knowledge configurations. Abbreviations: CG, control group; EG1, Experimental Group 1; EG2, Experimental Group 2. (a–c) Different team decision-making processes. (a) The prototypical decision-making process in a human team. (b) EG1, where teams collaborated with AI with centralized knowledge. (c) EG2, where teams collaborated with AI with asymmetric knowledge.

collaboration is limited, with inconclusive findings on whether AI improves teaming processes and team performance (Zercher et al. 2023). Specifically, for teams with distributed knowledge, where asymmetries during team decision-making often hinder accurate decisions (Brodbeck et al. 2007), generative AI's analytical and collaborative capabilities can reduce these asymmetries. However, AI also poses new challenges, because humans must effectively collaborate with the AI team members to benefit from AI knowledge. This can result in the emergence of new asymmetries unique to team–AI collaboration. Therefore, benefiting from AI team members in team–AI collaboration implies two mechanisms: (1) improving decision-making processes compared to human teams by reducing asymmetries during team decision-making and (2) effectively engaging with AI team members to integrate AI knowledge into the team's decision-making process. Drawing on the IAM, we investigated how the AI's knowledge configuration affects known asymmetries in decision-making (negotiation focus and shared information bias) and explored new asymmetries in collaboration with the AI team member (AI collaboration focus, AI information processing, and trust in AI team members).

In line with our hypotheses, teams collaborating with AI team members show a reduced negotiation focus and a shared information bias compared to human teams. Further, teams collaborating with AI team members with centralized knowledge benefit more than those with asymmetric knowledge, make more accurate decisions, and demonstrate stronger mitigation of asymmetries during team decision-making. Answering our exploratory research questions, we found that the emergence of asymmetries during team–AI collaboration depends on the knowledge of the AI team member. Teams collaborating with AI team members with asymmetric knowledge engage in a more critical collaboration focus with the AI team member compared to teams collaborating with AI team members with centralized knowledge. Similarly, teams collaborating with AI team members with asymmetric knowledge process AI information more intensively than teams collaborating with AI team members with centralized knowledge but tend to reject AI suggestions more frequently and rely less on AI information. This might explain why teams collaborating with AI team members with asymmetric knowledge do not make more accurate decisions than human teams, whereas teams collaborating with AI team members with centralized knowledge experience a significant increase in decision accuracy. This difference seems to be the result of distrust in AI team members with asymmetric knowledge, stemming from the lack of social validation for unshared AI knowledge. To capture these asymmetries, we developed three process models.

5.1 | Theoretical Implications

Our study offers various theoretical implications. First, previous research on human–AI collaboration has mainly focused on how individuals can successfully collaborate with AI (Lyons et al. 2021; O'Neill et al. 2022; Zercher et al. 2023). Further, the limited prior team–AI collaboration research is inconclusive on whether AI improves team processes and outcomes (Zercher et al. 2023). By applying the IAM (Brodbeck et al. 2007), our study illustrates how human teams can benefit from AI team members' knowledge, particularly in scenarios where human teams with distributed knowledge struggle to make accurate decisions (Brodbeck et al. 2007). We found that teams collaborating with AI team members show reduced asymmetries during team decision-making compared to human teams, demonstrating a more complex decision-making process. However, the benefits of AI team members in terms of decision accuracy and bias mitigation depend on their knowledge configuration, with centralized AI knowledge providing the most significant improvements. In contrast, human teams collaborating with AI team members that have asymmetric knowledge show similarities to human teams in their strong reliance on prediscussion preferences, often leading to inaccurate team decisions despite increased information exchange. Therefore, our study highlights that AI knowledge plays a critical role in effectively reducing asymmetries in team decision-making. Specifically, our findings show that, in order to correct false preferences, AI team members need to provide comprehensive and transparent information; otherwise, individuals typically rely more on human consensus. This implies that future theory development on team–AI collaboration should account for the AI's knowledge to understand how AI team members can improve team decision-making (Bankins et al. 2024).

Second, there is currently a limited understanding of how human teams handle challenges related to opaque AI knowledge, incomplete or false AI information, and how these factors impact decision quality (Bankins et al. 2024; Zercher et al. 2023). Therefore, we have extended the IAM (Brodbeck et al. 2007) to address new asymmetries specific to team–AI collaboration. These include AI collaboration focus, AI information processing, and trust in AI team members rooted in social validation. This extension provides a more detailed understanding of the additional factors necessary for successful collaboration. Our findings indicate that social validation might be a critical factor in explaining why these asymmetries in collaboration with AI team members emerge. Teams collaborating with AI team members that have asymmetric knowledge cannot fully validate the AI's knowledge. The IAM suggests that humans perceive shared information, which is eligible for social validation, as more reliable and valid than unshared information, which lacks this validation (Brodbeck et al. 2007; Greitemeyer and Schulz-Hardt 2003; Mojzisch et al. 2010). This is also reflected in the video, where teams collaborating with AI team members with asymmetric knowledge are often more surprised by unshared AI information than by unshared human information. This surprise seems to prompt intense discussions and collaboration to comprehend the information. However, the inability to fully validate asymmetric AI knowledge appears to weaken trust in AI team members and increase skepticism. This might explain why teams collaborating with AI team members with asymmetric knowledge rely on their initial preferences rather than on information provided by the AI team members. It also helps explain their critical AI collaboration focus and nonbeneficial AI information processing in these teams. Interestingly, in teams collaborating with AI team members with asymmetric knowledge, the lack of social validation for the AI team member's unshared information seems to have a strong impact on team decisions. In contrast, the AI team member's validation of team members' suboptimal prediscussion preferences appears to be less influential. Drawing on social identity theory, AI team members might not be perceived as being on the same level as a human team member, making human validation more influential (Tajfel 1982). Additional data from our study suggest that teams in both AI knowledge configurations perceived AI team members significantly more as tools than as team members (Appendix G). Although we clearly introduced the AI as a team member at the start of the experiment, our findings indicate that these differential social categorizations of AI and human team members affect how information validation influences the team decision-making process. This might increase the need for social validation of AI team members, as they are perceived more as error-prone tools than as trustworthy team members. Thus, our findings also contribute to a better understanding of the role of AI in team decision-making by illustrating that despite generative AI's advanced cognitive and collaborative capabilities—which enable it to actively participate in team discussions and decision—making it is still predominantly perceived as a tool. This suggests that current conceptualizations of AI as team members do not fully align with subjective perceptions, which may prioritize social skills, empathy, or shared experiences.

Third, our exploratory process models highlight how AI team members can simultaneously exhibit two conflicting effects: on the one hand, typical asymmetries in human teams are reduced; on the other hand, teams must address new asymmetries that arise from using and socially processing information provided by the AI team member. This offers a foundation for future confirmatory studies to test the proposed temporal processes. For instance, using social information processing theory, which posits that individuals adapt their behavior based on available social cues and information, could provide a complementary perspective to develop a more profound understanding of the asymmetries emerging in team–AI collaboration (Salancik and Pfeffer 1978). We observed that asymmetric AI knowledge, combined with human team members' reactions, leads to asymmetries during the collaboration with AI, such as increased advice-seeking, questioning, and rejection of AI advice. This behavior might result from social information processing, where uncertainty about the AI team member's correctness prompts additional scrutiny. Therefore, by extending the IAM (Brodbeck et al. 2007) to AI-specific asymmetries, future studies can investigate how the social information processing of AI prompts, AI responses, and human team members' reactions contribute to the emergence of these asymmetries specific to team–AI collaboration.

5.2 | Practical Implications

Our study also offers several practical insights. First, we found that the degree to which AI team members can mitigate asymmetries during team decision-making and improve the accuracy of team decisions is contingent on the AI team members' knowledge configuration. This has significant practical implications for managers seeking to effectively integrate AI team members into their teams. Generally, AI team members with centralized knowledge are most beneficial for team decision accuracy and asymmetry mitigation. However, publicly available AI is often not tailored to specific decision tasks. Our findings illustrate that, despite the AI's advanced capabilities and an elaborate decision-making process, integrating AI team members into a human team with distributed knowledge does not automatically lead to better decisions. The reason for this is that the effectiveness of team–AI collaboration is influenced by the alignment between the AI team member's knowledge and the team's knowledge, which is crucial to facilitate social validation. Therefore, managers should aim to understand the knowledge structures existing in their teams, the specific capabilities and limitations of the AI, and the nature of the decision tasks at hand. Such an understanding enables managers to select and tailor AI to complement the team's knowledge and decision-making patterns. For instance, ensuring that an AI team member's knowledge is comprehensive and easily verifiable by human team members can enhance trust and collaboration, leading to improved decision accuracy.

Second, recognizing that social validation is central to developing trust in AI team members—and that this might shape asymmetries during collaboration with AI—has important implications for how teams need to be trained to collaborate with AI team members (DeChurch and Marks 2006; Ulfert et al. 2024). Generally, relying on social validation can be a functional mechanism for managing the risk of incomplete or false AI information, especially if users lack metaknowledge about the information available to the AI (Fügener et al. 2022). This is often the case in reality due to the black-box nature of AI, which in turn poses a significant challenge to collaboration with generative AI (Łabuz and Nehring 2024). In our experiment, we observed that the critical evaluation of unshared AI information resulted in teams not benefiting from the AI team member's decision-relevant complementary knowledge, which explains the teams' inaccurate decisions. Thus, managers should encourage teams not to rely solely on social validation but also to consider other sources such as organizational data or original sources in validating AI information. Further, introducing AI team members should include training on how to effectively collaborate with them, along with information about their capabilities and limitations. With that, managers can prevent both distrust of and overreliance on AI team members, fostering more beneficial team–AI collaboration (Glikson and Woolley 2020; Ulfert et al. 2024).

5.3 | Limitations and Future Research Directions

Our study has limitations that open opportunities for future research. First, as an exploratory study, we aimed to identify key topics in team–AI collaboration. Further investigation is needed to refine and consolidate our extension of the IAM model, which includes asymmetries specific to team–AI collaboration—particularly AI collaboration focus, AI information processing, and trust in AI team members rooted in social validation. This is especially relevant to individual evaluations of information, such as preference consistency and information ownership (Mojzisch et al. 2010). Similarly, future research should explore social validation by examining varying amounts of unshared AI knowledge and how human team members validate or invalidate it.

Second, although we controlled for team composition variables such as educational background, gender diversity, or team size across experimental conditions (e.g., Kearney et al. 2022), we did not concentrate on team diversity in this study. In our experiment, introducing AI team members in different knowledge configurations resulted in varying team sizes. We accounted for this in our statistical analysis; however, it remains unclear how team size variations might affect teaming processes in team–AI collaboration. Future research should investigate how team characteristics like team composition affect team–AI collaboration (Waldman and Sparr 2023).

Third, regarding our methods, the study's specificity limits its generalizability to other forms of AI team members, repeated collaborations, or different task types. We used a text-based conversational agent (ChatGPT), but models like GPT-4 Omni, with multimodal capabilities and a proactive interaction style, could support broader collaborations extending to design, creative work, and manual tasks. Although the introductory message and conversational design framed chatbot Alex as part of the decision-making team, participants perceived Alex more as a tool than a team member. Future research should explicitly investigate how the perception of AI as a team member in team decision-making is shaped by different teaming capabilities, interaction modalities, communication styles, and embodiments. For example, requiring interaction with the AI team member at specific decision points or incorporating voice-based communication or physical embodiment could strengthen the perception of Alex as a team member. Finally, although our study focused on hidden profile tasks within horizontal teams, future research could investigate leadership in team–AI collaboration within vertical team structures (e.g., Kelemen et al. 2023).

6 | Conclusion

In our study, we draw on and extend the IAM to investigate how human teams collaborating with AI team members can achieve more accurate decisions by considering both collaboration among humans and collaboration with the AI team member. Through a mixed-methods laboratory experiment, we reveal that teams collaborating with AI team members with centralized knowledge make more accurate decisions than human teams. These teams have fewer decision-making asymmetries than those collaborating with AI team members with asymmetric knowledge. To explain this difference, we identify asymmetries in collaboration with AI team members—specifically, AI collaboration focus, AI information processing, and trust in AI rooted in social validation—thereby extending the IAM. We found that teams collaborating with AI team members with asymmetric knowledge display collaboration asymmetries with the AI team member, characterized by a critical collaboration focus, low trust in the AI team member due to lacking social validation, and non-beneficial AI information processing. Our findings highlight the importance of developing new theories on team–AI collaboration that consider both collaboration among human team members and collaboration with AI team members, as well as AI knowledge, to explain how teams can benefit from AI team members during decision-making.

Acknowledgments

This work was supported by the German Federal Ministry for Digital and Transport (45FGU140_B) and the Karin-Islinger-Stiftung. Open Access funding enabled and organized by Projekt DEAL.

Ethics Statement

All procedures performed in this study involving human participants were in accordance with the ethical standards of the institutional and/or national research committee and with the European General Data Protection Regulation. Informed consent was obtained from all participants.

Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

The data supporting the findings of this study and the Python code for the chatbot Alex are available from the authors upon request.

Endnotes

[1] Team–AI collaboration specifically refers to a team of humans working alongside an AI team member, whereas the broader term "human–AI collaboration" or related concepts like human-autonomy teaming often focus on human–AI dyads, where one human collaborates with one AI (Zercher et al. 2023).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.

Appendix A

Item Scales

Control Variables

TABLE A1 Disposition to trust on a 5-point Likert scale adapted from Gefen (2000).

Item
I generally have faith in humanity.
I feel that others are generally reliable.
I generally trust others unless they give me a reason not to.

TABLE A2 Disposition to trust the AI on a 5-point Likert scale adapted from Gefen (2000).

Item
I generally have faith in AI.
I feel that AI are generally reliable.
I generally trust AI unless they give me a reason not to.

TABLE A3 Prior experience with AI, teams, and chatbots on a 5-point Likert scale.

Item
I am experienced in the use of AI.
I am experienced in teamwork.
I am experienced in the use of chatbots.

Manipulation Checks

TABLE A4 Information recall Schulz-Hardt et al. (2006).

Item
What are the attributes of Alpha?
What are the attributes of Beta?
What are the attributes of Gamma?
What are the attributes of Delta?

Decisions

TABLE A5 Prediscussion preferences, Schulz-Hardt et al. (2006).

Item
In your personal opinion, which candidate is best suited for the pilot position?

TABLE A6 Decision accuracy.

Item
Which candidate did your group choose?

TABLE A7 Trust in the AI regarding competence, benevolence, and integrity adapted from Benbasat and Wang (2005).

Item
The AI Alex was like a real expert in assessing the candidates.
The AI Alex had the expertise to understand my needs and preferences regarding the candidates.
The AI Alex was able to understand my needs and preferences regarding the candidates.
The AI Alex had good knowledge of the candidates.
The AI Alex considered my needs and all the important characteristics of the candidates.
The AI Alex prioritized my interests.
The AI Alex kept my interests in mind.
The AI Alex wanted to understand my needs and preferences.
The AI Alex was impartial.
The AI Alex was honest.
I consider the AI Alex to be decent.

Appendix B

Pretest of Candidate Attributes

TABLE B1 Descriptive statistics on attributes level of the candidate information pretest.

	Valence		Strength	
Candidate	**M**	**SD**	**M**	**SD**
Alpha				
Has a very good sense for recognizing dangerous situations	4.60	0.61	4.65	0.77
Has a good overview of complex contexts	4.66	0.56	4.48	0.76
Has excellent spatial awareness	4.48	0.68	4.59	0.76
Is very well organized	4.49	0.06	4.38	0.70
Sometimes does not tolerate criticism	1.87	0.71	3.15	1.21
Is sometimes a bit hectic	2.17	0.68	3.18	1.03
Is considered a show-off	2.19	0.69	2.48	1.01
Is not open to new ideas	2.04	0.79	3.12	1.06
Is unfriendly	1.73	0.64	2.83	1.04
Transmits restlessness	1.71	0.68	3.39	1.26
Beta				
Keeps a cool head in crisis situations	4.81	0.47	4.80	0.48
You can rely on him/her 100%	4.78	0.50	4.68	0.64
Can assess weather conditions very well	4.33	0.86	4.51	0.80
Is good at multitasking	4.49	0.76	4.43	0.82
Is considered to be nagging	2.13	0.66	2.46	0.85
Is not considered very cooperative	1.76	0.85	3.42	1.12
Has a below-average memory for numbers	2.22	1.05	3.35	1.13
Gossips about his/her coworkers	1.67	0.57	2.75	1.08
Is considered arrogant	2.05	0.68	2.54	0.91
Is sometimes abusive in tone	2.01	0.66	2.80	1.03

Candidate	Valence		Strength	
	M	SD	M	SD
Gamma				
Can make the right decisions very quickly	4.74	0.57	4.61	0.78
Is stress resistant	4.77	0.49	4.65	0.67
Promotes a good atmosphere within the crew	4.45	0.61	4.12	0.69
Is very conscientious	4.58	0.63	4.51	0.67
Is very skilled in dealing with complicated technology	4.68	0.59	4.57	0.69
Puts the safety of people in his/her care above everything else	4.58	0.64	4.53	0.80
Performs very well in terms of sustained attention	4.80	0.40	4.73	0.59
Is not verbally skillful	2.41	0.64	2.73	0.93
Is considered egocentric	2.01	0.68	2.56	0.97
Is reluctant to take part in training	1.91	0.70	3.12	1.17
Delta				
Can react adequately to unforeseen events	4.71	0.48	4.73	0.62
Can concentrate very well	4.73	0.57	4.66	0.75
Is very resilient	4.63	0.54	4.57	0.80
Is very responsible	4.63	0.52	4.63	0.70
Is considered arrogant	2.03	0.65	2.65	1.01
Is not very well suited for leading a team	2.05	0.91	3.43	1.21
Is considered to be know-all	2.29	0.65	2.37	0.88
Is quick-tempered	1.90	0.67	3.10	1.05
Is considered moody	1.97	0.68	2.82	0.95
Has strong prejudices	1.70	0.67	2.95	1.22

TABLE B2 Descriptive statistics on candidate level of the candidate information pretest split into positive and negative information.

Candidate	Valence		Strength		Interaction
	M	SD	M	SD	
Total					
Alpha	3.00	0.61	3.63	0.96	10.86
Beta	3.03	0.71	3.57	0.89	10.81
Gamma	3.89	0.60	4.01	0.79	15.62
Delta	3.07	0.63	3.59	0.92	11.00
Positive					
Alpha	4.56	0.48	4.53	0.74	20.63
Beta	4.60	0.65	4.60	0.68	21.19
Gamma	4.66	0.56	4.53	0.70	21.10
Delta	4.68	0.53	4.65	0.72	21.74

Candidate	Valence		Strength		Interaction
	M	SD	M	SD	
Negative					
Alpha	1.95	0.70	3.03	1.10	5.91
Beta	1.97	0.74	2.89	1.02	5.70
Gamma	2.11	0.67	2.80	1.02	5.92
Delta	1.99	0.70	2.88	1.05	5.74

Appendix C

Experimental Material

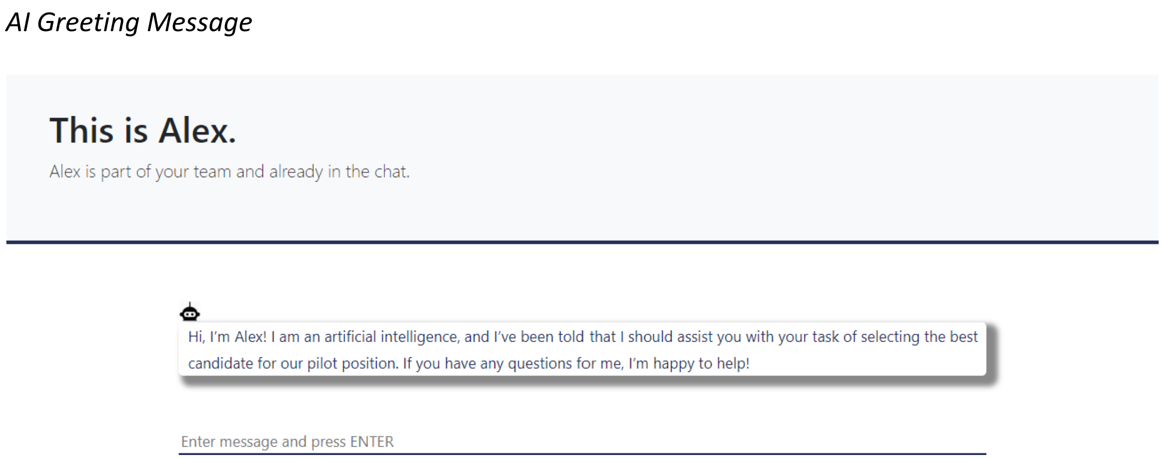

FIGURE C1 *Note:* Translated from German to English.

We fine-tuned the API parameter temperature to 0.1 to ensure that the AI responded appropriately to the decision context. Lower temperature values typically result in more conservative and contextually appropriate responses, which is beneficial as we need the AI to adhere closely to the specific decision context and generate more predictable outputs. However, considering the generative nature of the AI, the chatbot was allowed to incorporate additional attributes mentioned during the conversation. It was not restricted to how humans interact with it, thereby enabling participants to experience the flexibility of interacting with generative AI as part of our exploratory method to create a more realistic setting.

Appendix D

Results of the Control Variables and Manipulation Checks

TABLE D1 Distribution of gender and highest educational level across all groups.

Demographic characteristic	CG		EG1		EG2	
	n	%	*n*	%	*n*	%
Gender						
Female	25	33.33	33	39.28	17	30.35
Male	50	66.66	51	60.71	39	69.64
Highest educational level						
A level	39	52.00	52	61.90	22	39.28
Specialized A level	1	1.33	1	1.19	0	0.00
Bachelor	29	38.66	26	30.95	24	42.85
Master	6	8.00	4	4.76	7	12.50
Diploma	0	0.00	0	0.00	1	1.78
Other	0	0.00	1	1.19	2	3.57

TABLE D2 Descriptive statistics of the age and control variables across all groups.

	CG		EG1		EG2	
Demographic characteristic	**M**	**SD**	**M**	**SD**	**M**	**SD**
Age	2.42	3.15	24.36	4.37	26.05	4.96
Control variables						
I generally have faith in humanity.	3.69	0.96	3.64	0.87	3.52	0.89
I feel that others are generally reliable.	3.39	0.79	3.60	0.78	3.34	0.82
I generally trust others unless they give me a reason not to.	4.15	0.69	4.10	0.85	3.93	0.89
I generally have faith in AI.	3.27	0.72	3.15	0.65	3.11	0.85
I feel that AI is generally reliable.	3.17	0.91	3.05	0.86	2.96	0.87
I generally trust AI unless given a reason not to.	3.52	0.99	3.23	1.01	3.11	1.00
I am experienced in the use of AI.	3.48	1.02	3.00	1.15	3.14	1.24
I am experienced in teamwork.	4.28	0.75	4.32	0.69	4.16	0.78
I am experienced in the use of chatbots.	3.72	1.03	3.50	1.14	3.63	1.11

Note: There was no significant difference between conditions in these control variables, except that the CG showed more experience in working with AI than EG1 did. This difference is not problematic because collaboration with AI was not measured in the CG and was only compared between EG1 and EG2. Further, no conditions showed any difference in their use of chatbots, which is more central to our study.

TABLE D3 Descriptive statistics of the ability to remember candidate information.

				95% CI	
		M	**SD**	***LL***	***UL***
Recall alpha	CG	2.43	1.49	2.08	2.77
	EG1	2.55	1.45	2.23	2.86
	EG2	2.62	1.58	2.22	3.07
Recall beta	CG	2.51	1.56	2.15	2.87
	EG1	2.71	1.53	2.38	3.05
	EG2	2.70	1.62	2.26	3.13
Recall gamma	CG	2.53	1.65	2.15	2.91
	EG1	2.81	1.75	2.43	3.19
	EG2	2.68	1.61	2.25	3.11
Recall delta	CG	2.23	1.49	1.89	2.57
	EG1	2.10	1.29	1.81	2.38
	EG2	2.04	1.26	1.70	2.37

Appendix E

Additional Controls and Information

Table E1 gives a summary of the descriptive statistics of discussion participation. Participants in EG2 and CG did not differ in their discussion participation, and their discussion focuses on certain candidates (mentioned and repeated, $p > 0.05$). In EG1 and EG2, however, Team Member Y mentioned significantly more candidate information than the other team members post-AI. The video analysis revealed that this was due to Participant Y sitting in front of the laptop and reading the candidate information of the AI to the other participants.

TABLE E1 | Descriptive statistics for discussion participation of the participants.

	CG		EG1				EG2			
			Pre-AI		Post-AI		Pre-AI		Post-AI	
Participants	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Mentioned information in %										
X	15.76	18.57	8.10	9.36	20.40	10.27	10.00	12.25	20.00	13.05
Y	13.59	14.94	5.90	8.10	24.70	8.71	11.70	13.29	30.34	17.85
Z	17.07	19.69	5.50	6.79	18.50	11.41	—	—	—	—
Repeated information										
X	0.21	0.21	0.03	0.04	0.22	0.17	0.05	0.06	0.31	0.40
Y	0.22	0.20	0.02	0.03	0.25	0.15	0.07	0.09	0.29	0.33
Z	0.25	0.28	0.03	0.04	0.20	0.14	—	—	—	—

Note: Mean (M) and standard deviation (SD) for the different participants' (X, Y, Z) discussion participation (mentioned and repeated) for pre- and post-AI participation. Values have been normalized to the number of teams in each condition.

TABLE E2 Formulas for the measure of discussion participation.

Formula		
Discussion participation		
Average number of a participant's mentioned information items	$\frac{\sum \textit{mentioned information of a participant of a condition}}{\textit{number of teams of a condition}}$	(E1)
Average number of repetitions of all a participant's mentioned information items	$\frac{\sum \textit{repeated information of a participant of a condition}}{\textit{number of teams of a condition}}$	(E2)

TABLE E3 Descriptive statistics for discussion focus on certain candidates.

	CG		EG1				EG2			
			Pre-AI		Post-AI		Pre-AI		Post-AI	
Candidate	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**	**M**	**SD**
Mentioned information in %										
Alpha	53.48	17.18	21.60	8.62	62.40	13.53	28.18	17.46	46.82	19.40
Beta	43.48	16.50	19.60	7.68	68.40	6.80	22.27	14.86	24.95	19.58
Gamma	48.70	28.96	21.60	12.03	73.60	13.05	20.91	18.65	49.09	31.02
Delta	40.00	10.07	15.20	8.54	50.00	9.67	15.45	11.54	52.73	22.75
Repeated information										
Alpha	0.73	0.43	0.07	0.07	0.52	0.19	0.15	0.12	0.55	0.60
Beta	0.76	0.32	0.07	0.06	0.64	0.21	0.12	0.11	0.85	0.55
Gamma	0.62	0.70	0.08	0.10	1.03	0.54	0.14	0.17	0.68	0.58
Delta	0.63	0.30	0.06	0.05	0.48	0.25	0.04	0.05	0.78	0.55

Note: Mean (M) and standard deviation (SD) for the discussion focus (mentioned information and repeated information) on certain candidates and for pre- and post-AI participation. Values have been normalized to the number of teams in each condition.

TABLE E4 Formulas for the measures of discussion focus.

	Formula	
Discussion focus		
Average number of a candidate's mentioned information items	$\frac{\sum \textit{information mentioned of a candidate of a condition}}{\textit{number of teams of a condition}}$	(E3)
Average number of repetitions of all a candidate's mentioned information items	$\frac{\sum \textit{repeated information of a candidate of a condition}}{\textit{number of teams of a condition}}$	(E4)

TABLE E5 Shapiro–Wilk and Levene test for the reported parameters in all groups.

Parameters	Shapiro–Wilk	Levene
Trust in AI team members	0.018	0.879
Discussion intensity	< 0.001	0.061
Shared information mentioned	0.025	0.428
Unshared information mentioned	0.037	0.315
Shared information repeated	< 0.001	< 0.001
Unshared information repeated	< 0.001	< 0.001
Timespan using AI	< 0.001	0.861
AI prompt intensity	< 0.001	0.034
AI repetitions	< 0.001	< 0.001
Weighting	< 0.001	0.497
Advice	< 0.001	0.019
Explanation	< 0.001	0.412
Aggregation	< 0.001	0.033
Giving AI attributes	< 0.001	0.062
Questioning AI	< 0.001	0.047
Prediscussion correspondence	< 0.001	< 0.001

TABLE E6 | Distribution of prediscussion preferences in % for all candidates.

		Alpha	Beta	Gamma	Delta
Knowledge configuration	CG	22.7	40.0	18.7	18.7
	EG1	17.9	28.6	27.4	26.2
	EG2	19.6	30.4	21.4	28.6
	Overall	20.0	33.0	22.8	24.2

Table E6 provides an overview of prediscussion preferences for each candidate in the different knowledge configurations. Table E6 shows the prediscussion preferences for certain candidates in the different conditions. Candidate Beta was the consistently preferred choice in all knowledge configurations, followed by Delta and Gamma, with Alpha being the least preferred option before the discussion according to our hidden profile. A χ^2-test demonstrated that there is no significant relationship between the experimental group and the preference for a certain candidate ($\chi^2[6] = 5.11$, $p = 0.53$, $\varphi = 0.15$).

TABLE E7 Average mentioned and repeated information in all groups.

	CG		EG1		EG2	
Category	**M**	**SD**	**M**	**SD**	**M**	**SD**
Mentioned information in %	46.4	20.1	79.8	16.1	69.0	24.2
Repeated information	0.68	0.47	0.74	0.44	0.83	0.58

Timespan Using AI

Before assessing the AI use intensity, we controlled to ensure that teams in EG1 (M = 3.56, SD = 2.53) and EG2 (M = 4.11, SD = 2.56) did not differ in how fast they incorporated the AI into the team discussion ($U = 249.500$, $Z = -0.31$ $p = 0.76$).

Preregistration

During the revision process, the research questions were refined into hypotheses and research questions (https://osf.io/wqdum?view_only=5d9cf99e66314023af1e428b9fe26feb).

Appendix F

Measures

TABLE F1 Formulas for the measures of intensity and shared information bias.

	Formula	
Discussion intensity		
Average number of a group's mentioned information items	$\frac{\sum \textit{mentioned information of a condition}}{\sum \textit{team in condition} + \textit{number team members}}$	(F1)
Average number of repetitions of all of a group's mentioned information items	$\frac{\sum \textit{repeated information of a condition}}{\sum \textit{team in condition} + \textit{number team members}}$	(F2)
Discussion intensity	$\frac{\sum \textit{repeated information} + \sum \textit{mentioned information}}{\sum \textit{team in condition} + \textit{number team members}}$	(F3)
Shared information bias		
Completeness of mentioning shared information	$\frac{\textit{number of shared information mentioned}}{\textit{total number of shared information}}$	(F4)
Completeness of mentioning unshared information	$\frac{\textit{number of unshared information mentioned}}{\textit{total number of unshared information}}$	(F5)
Bias toward mentioning shared information	$\frac{F4}{\mathrm{F4}+\mathrm{F5}}$	(F6)
Repetition rate of shared information	$\frac{\sum \textit{repetiton of shared information}}{\textit{total number of shared infomation}}$	(F9)
Repetition rate of unshared information	$\frac{\sum \textit{repetiton of shared information}}{\textit{total number of shared infomation}}$	(F10)
Bias toward repeating shared information	$\frac{F9}{\mathrm{F9}+\mathrm{F10}}$	(F11)

Appendix G

Additional Figures and Results

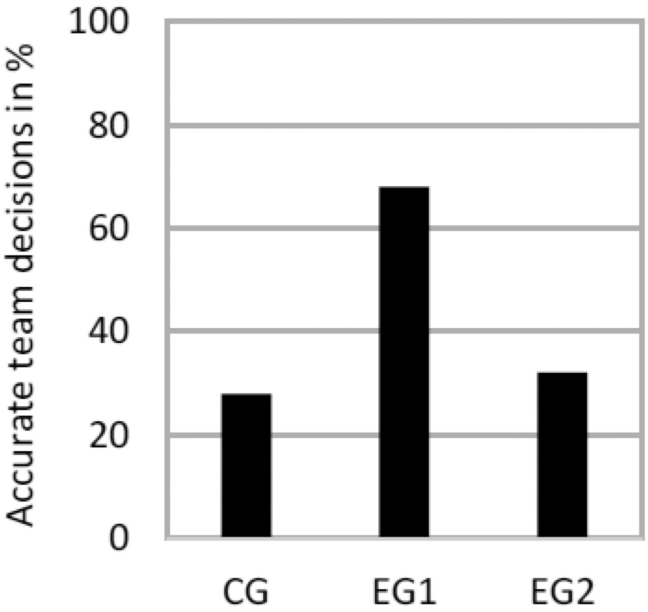

FIGURE G1 Accuracy of the team decision.

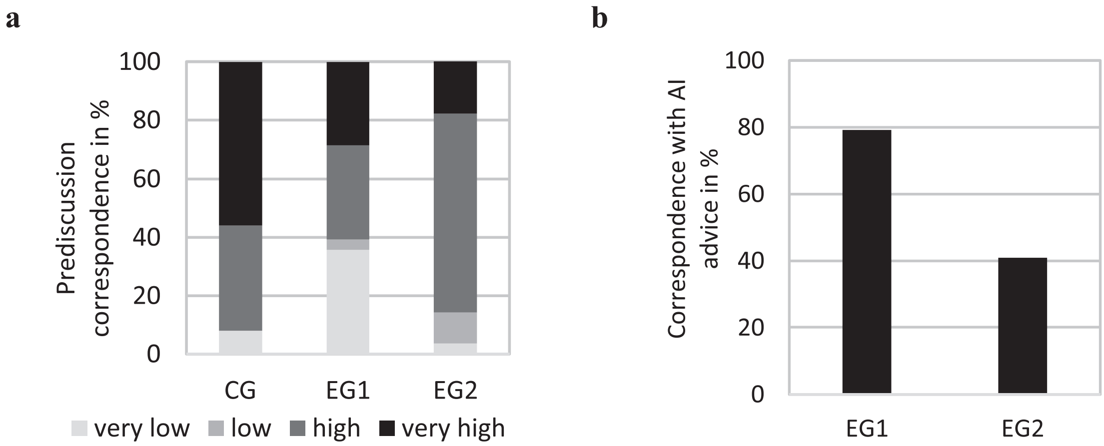

FIGURE G2 | Degree of prediscussion correspondence for the final team decision (a) and correspondence of team decisions with AI advice (b). *Note:* Very high: Two participants preferred the selected candidate; high: One participant preferred the selected candidate; low: No participant preferred the selected candidate; very low: Two participants jointly preferred a different candidate.

Average Perceived AI Team Membership

Interestingly, participants perceived AI as a tool (M = 4.17, SD = 0.85) rather than as a team member (M = 2.42, SD = 1.22). Given that the data were not normally distributed, a nonparametric Wilcoxon signed-rank test was conducted. This test revealed that these differences are statistically significant, with a test statistic of $Z = -9.28$ and a p value of less than 0.001. The effect size was $r = 0.79$, indicating a large effect. This suggests that the perception of AI as a tool rather than a team member is a robust finding across participants, reflecting a strong general tendency to view generative AI as fulfilling a functional and instrumental role rather than collaborative partner role in a team–AI collaboration setting. The teams in the two AI knowledge configurations did not differ in their perception of AI as a tool or team member ($p > 0.05$) (see also Zercher et al. 2025).