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Chatbot Catalysts: Improving Team Decision-Making Through Cognitive Diversity and Information Elaboration

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Completed Research Paper

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Abstract

As the integration of artificial intelligence (AI) into team decision-making continues to expand, it is both theoretically and practically pressing for researchers to understand the impact of the technology on team dynamics and performance. To investigate this relationship, we conducted an online experiment in which teams made decisions supported by chatbots and employed computational methods to analyze team interaction processes. Our results indicated that compared to those assisted by chatbots in later phases, teams receiving chatbot assistance during the initial phase of their decision-making process exhibited increased cognitive diversity (i.e., diversity in shared information) and information elaboration (i.e., exchange and integration of information). Ultimately, teams assisted by chatbots early on performed better. These results imply that introducing AI at the beginning of the process can enhance team decision-making by promoting effective information sharing among team members.

Keywords: Artificial intelligence, team decision-making, cognitive diversity, temporal dynamics

Introduction

Artificial intelligence (AI) has emerged as a vital component of modern society, necessitating a deeper exploration into the ways humans collaborate with AI systems in order to accomplish tasks effectively. AI refers to a collection of technologies that possess the capacity to execute cognitive functions analogous to the human mind (Russel and Norvig, 2009). These functions include gathering information from external sources, analyzing the collected data to discern patterns or generate predictions, and evaluating the outcomes to refine their decision-making algorithms (Malone, 2018). Given the growing adoption of AI systems in decision-making across a wide range of domains, such as hiring decision-support tools (Van den Broek et al., 2021), creativity support systems (Mikalef and Gupta, 2021), medical decision support systems (Yang et al., 2019; Lebovitz et al., 2022), and strategic marketing decision-support mechanisms (Enholm et al., 2021), it is imperative to explore the potential impact of AI on team decision-making processes. By understanding the impact of AI on collaborative decision-making, researchers and developers can enhance the design, development, and integration of intelligent technologies within teams. This, in turn, can lead to more effective and efficient collaboration, resulting in improved problem-solving and decision-making capabilities.

AI, encompassing chatbots, virtual assistants, and machine learning algorithms, possesses the potential to bolster human cognition and enhance team decision-making through its advanced cognitive capabilities. Although recent studies have started to investigate the ways individuals might employ AI-generated advice (Dietvorst et al., 2016; Logg et al., 2019; Reich et al., 2022), there remains a significant gap in the examination of AI's impact on team decision-making (Sebo et al., 2020; Yan and Gurkan, 2023). This dearth of research can be ascribed to the complex nature of teams, which are composed of interdependent components, such as members, and exhibit dynamic interaction processes, including information sharing (Arrow et al., 2000). Consequently, AI can influence teams in intricate and emergent manners.

As an important paradigm in team research, studies of team decision-making have developed a rich theoretical tradition (De Dreu and West, 2001; Mell et al., 2014; Stasser and Titus, 2003; Wittenbaum et al., 2004). Building on this body of research, the present study aims to take a pioneering step toward understanding how AI may influence team decision-making by examining its impact on team information-sharing processes. Specifically, we explore how introducing AI assistance at different stages of team development affects information-sharing processes and, ultimately, the quality of team decisions. We concentrate on two information-sharing processes in decision-making: cognitive diversity and information elaboration. Cognitive diversity in teams concerns the range of information, information processing styles, and perspectives of members (Sauer et al., 2006). Information elaboration involves the exchange, discussion, analysis, and integration of information among team members (Mell et al., 2014; van Ginkel & van Knippenberg, 2008). Our findings indicate that the positive impact of chatbot assistance is more pronounced when the agent is introduced early in the team discussion. Further analysis reveals that teams receiving chatbot assistance during the initial stages of the decision-making task exhibited higher levels of information elaboration and cognitive diversity, thereby enhancing the information-sharing quality and decision-making outcomes.

Related Work

Artificial intelligence (AI), although not a novel concept, has gained significant attention in recent years due to its potential applications and advancements (Ransbotham et al., 2018). As organizations increasingly adopt AI applications, they expect benefits such as improved decision-making quality and enhanced collaboration (Uren and Edwards, 2023). However, despite the growing interest in AI, numerous companies and organizations grapple with harnessing its value (Fountaine et al., 2019). Even when organizations invest considerable time, effort, and resources into the adoption process, the anticipated benefits of AI may remain elusive (Makarius et al., 2020).

To improve the integration of AI in decision-making tasks, researchers have focused on examining the degree to which humans can trust intelligent agents (You and Robert, 2018) and assessing the potential impacts of these technologies on team interaction (Sebo et al., 2020). Consequently, they have proposed human-centered mechanisms to effectively incorporate AI into teams, thereby promoting appropriate reliance on AI advice (Hemmer et al., 2022). By examining the factors and the ways in which these intelligent technologies may influence various aspects of team dynamics, researchers aim to gain a deeper understanding of their potential roles in optimizing decision-making processes and fostering effective collaboration among team members (Seeber et al., 2020).

In recent years, researchers have examined their potential applications in management decision-making (Ferreira et al., 2021), collaborative idea generation (Hwang and Won, 2021), and as facilitators in collaborative tasks (Winkler et al., 2019). A particular area of interest has been the investigation of text-based AI systems and their potential advantages in various team tasks (Avula et al., 2018; Toxtli et al., 2018). For example, interactions with chatbots have been shown to improve group members' commitment to collective decisions by fostering a sense of shared effort and fairness, even when confronted with decisions that conflict with personal opinions (Shin et al., 2022). Likewise, these intelligent technologies can enhance individual satisfaction by promoting equitable participation and effective communication (Kim et al., 2020). Furthermore, virtual assistant tools can streamline decision-making in large, heterogeneous teams by incorporating cognitive mechanisms that support agreement and mitigate bias (Pèrez et al., 2018).

Despite the critical effect of the temporal stage on team dynamics (Arrow et al., 2000; Mathieu and Zaccaro, 2001; Gersick, 1988; Tuckman and Jensen, 1977), researchers have yet to examine the impact of temporality on AI's influence on team dynamics. To address this gap, we investigate the extent to which the timing of AI assistance influences information-sharing processes and, consequently, team decision-making quality. The current study advances the field by integrating theoretical perspectives from team research with emerging insights on human-AI team collaboration. In this context, our study also develops a computational model to analyze information-sharing processing, eliminating reliance on self-reports.

Theoretical Framework

As one of the routine tasks performed by teams in organizations (McGrath, 1984), collective decision-making entails exchanging, analyzing, and integrating information distributed among team members because members often possess different expertise and backgrounds and hold unique information regarding the decision at hand (Mell et al., 2014; Van Ginkel and Van Knippenberg, 2008). The present study employs the hidden profile paradigm (Stasser and Titus, 1985; Mell et al., 2014), which pertains to scenarios where a group's optimal decision relies on information distributed among all members. Within team research, the hidden profile paradigm simulates a situation in which information necessary to make the best team decision is present but distributed within the group(Stasser and Titus, 2003). Often, the unique, unshared information is overshadowed by shared knowledge, which all team members know. The challenge surfaces when teams, rather than pooling and integrating their unique insights, predominantly discuss commonly held information (Lu et al., 2012). Consequently, teams might arrive at decisions that, while appearing correct based on shared knowledge, are actually suboptimal when the entirety of available information is considered (Wittenbaum et al., 2004). This paradigm serves as a cautionary tale on the importance of effective communication and information sharing and emphasizes the potential pitfalls teams face when not harnessing their collective intelligence (Postmes et al., 2001).

The pattern of information distribution among team members matters since it can affect team interaction processes. Mell and colleagues (2014), for instance, found that when essential information from different knowledge areas is distributed among team members, teams tend to share less information and often make poorer decisions. This is because, with highly distributed information, each team member has access to a vast body of unique knowledge, which can make it challenging to understand what others are aware of and what they are not. Therefore, when information is highly distributed, unique details might not be mentioned because of social confirmation bias (Lu et al., 2012; Stasser and Titus, 2003). However, when multiple team members share the same information, it becomes more likely to be mentioned, prompting others to add more details. As a result, the team utilizes more of the information available to them, leading to better decision-making.

While years of team research have provided valuable insights into decision-making processes, Baird and Maruping (2021), have revisited traditional IS-based theories, culminating in a delegation-based framework for AI and human collaboration. This framework takes on added significance considering the challenges of metaknowledge: individuals frequently fail to accurately assess both their own and others' capabilities, which can lead to inferior decisions (Lebovitz et al., 2021; Fugner et al., 2021). AI has the potential to address challenges and enhance team decision-making by gathering the necessary information and streamlining information processes. However, the integration of advanced intelligent technologies may lead to alterations in team dynamics, as new technologies often present opportunities for structural changes within teams (Barley, 1986). These technologies can also affect the way team members assess their peers' expertise due to their sophisticated cognitive capabilities (Ward, 2013). Furthermore, the interactive features of AI can influence the patterns of interaction among team members (Lee et al., 2012). Consequently, AI assistance may have a significant impact on team processes and the overall quality of decision-making.

However, introducing new technology assistance can depend on the team's developmental stage, which influences members' collaboration and receptiveness to innovation. Teams constitute intricate systems consisting of numerous interdependent individuals working together to achieve a collective objective (Arrow et al., 2000). As members interact over time, shared team structures emerge, making temporal dynamics an essential aspect of team processes. For instance, compared to newly-formed teams, established teams may possess shared cognition such as transactive memory systems, which facilitate coordination but could positively or negatively affect their utilization of new technologies (Wegner, 1987; Yan et al., 2021; Yan and Gurkan, 2023). Studies also indicate that teams tend to change their interaction and coordination patterns significantly when they get to the temporal midpoint (Gersick, 1988; 1989).

Incorporating a new intelligent agent into team decision-making in different stages of a team task may produce varying effects on decision quality based on the timing of its implementation. Numerous studies have shown that people tend to imitate the behavior exhibited by intelligent technologies towards them (Oliveira et al., 2018; Strohkorb Sebo et al., 2018). This phenomenon can be explained by Social Learning Theory (Bandura, 1960), which posits that individuals can acquire new behaviors by observing others perform those actions. Consequently, teams may adopt the behaviors demonstrated by intelligent technologies, which could serve as a foundation for interactions among human counterparts. Nonetheless, this effect might not be observed in teams that have already established shared cognition, communication styles, and norms.

In particular, the timing of AI assistance may significantly influence team cognitive diversity, which is dynamically and interactively generated through communication. Team cognitive diversity is reflected in the extent to which the communication between group members in a given interaction is divergent rather than convergent (Cronin et al., 2011; Srikanth et al., 2016). This communication reflects interaction partners' structures of knowledge and interpretation (Foucault, 2002). The timing of AI assistance in teams may affect team cognitive diversity by influencing the likelihood that members will disseminate different mentioned and unmentioned information during team discussions. As the temporal midpoint approaches in team tasks, members become aware of the remaining time, they tend to modify their communication patterns to ensure the timely completion of tasks (Gersick, 1988; 1989). At the early stages of team collaboration, teams face relatively low stress to reach an agreement and are therefore more likely to share the unique information they possess if promoted by intelligent technology. By contrast, in the later stages, members may feel pressured to reach a consensus and make a final decision. Thus, members may be less likely to share different information even if it is directed by AI, leading to low cognitive diversity.

H1 Team cognitive diversity in decision-making is higher if AI assists the team at the beginning of the team collaboration than in the later stages.

For teams with distributed information, team cognitive diversity is important as it stimulates information elaboration—the exchange, discussion, and integration of task-relevant information (van Ginkel & van Knippenberg, 2008)— to find the optimal solution. AI assistance has the potential to significantly enhance team discussions and collective judgments by fostering information elaboration. However, the effectiveness of this catalyst varies among teams and depends on the temporal stage at which AI assistance is introduced. In later stages of team collaboration, teams may have already developed shared cognition, such as transactive memory systems, which can reduce their propensity for elaboration during discussions as members have developed interdependence on one another (Mell et al., 2014). Additionally, teams may have less time for elaboration as they approach the end of a task. Thus, introducing AI assistance in the later stages of team decision-making is less likely to promote information elaboration, resulting in a less collaborative and effective decision-making process than introducing AI early.

H2 Team information elaboration in decision-making is higher if AI assists the team at the beginning of the team collaboration than in the later stages.

We also expect that cognitive diversity and information elaboration serially mediate the effect of AI assistance timing on team performance. First, AI's impact on information elaboration can be explained by its influence on cognitive diversity. Teams with high cognitive diversity are more likely to engage in behaviors that stimulate team information elaboration because they are more likely to recognize the importance of information exchange to team performance (van Ginkel & van Knippenberg, 2008). The higher cognitive diversity a team has, the more complete that team's understanding of the knowledge accessible to the team and the distributed nature of this knowledge is. As van Ginkel and van Knippenberg (2008) have shown, realizing that different team members have unique expertise leads individuals to the understanding that the teams can benefit from exchanging and discussing this information (van Ginkel & van Knippenberg, 2008). As a result, they approach the team task from this perspective and more actively pursue information exchange and elaboration. In other words, high cognitive diversity makes information available for team discussion and collective judgment, thus promoting information elaboration.

High levels of cognitive diversity and information elaboration are essential for a team's decision-making quality and are likely to promote team performance (Mell et al., 2014; Sauer et al., 2006). Hidden profile tasks can profit from high cognitive diversity and sharing novel information during the information pooling process. Cognitive diversity fosters constructive discussions within teams, as it encourages members to challenge others' suggestions, justify their own positions when facing opposition, and explore contrasting perspectives to reach a solution (Simons et al., 1999). Therefore, heightened cognitive diversity is likely to enhance information elaboration – teams having a high cognitive diversity consciously seek information unknown to themselves, which makes it likely that they will indeed consider and process the obtained information and integrate it with what they already know. This process of information elaboration, in turn, has been consistently shown to be a key driver of the performance of teams with distributed information and a diversity of perspectives (Hoever et al., 2012; Homan et al., 2008). When teams exhibit greater cognitive diversity, a member sharing unique information may prompt others, who may be hesitant due to their own knowledge gaps, to also request information (Van Ginkel and Van Knippenberg, 2008). Moreover, witnessing a member successfully obtaining desired information can motivate others to exhibit similar behavior to fill gaps in their own understanding (Bandura, 1965). Consequently, these information-sharing processes lead teams to make better decisions.

H3 (**The Serial Mediation Hypothesis**) The effect of AI assistance timing on cognitive diversity subsequently predicts a) information elaboration and b) ultimately, team performance in decision-making.

Methods

To test our hypotheses, we conducted an online experiment in which teams of four performed a decision-making task. The experiment employed a 2 × 2 between-subject factorial design (N = 47). The first factor, *Chatbot Assistance* (first half vs. second half), varied the timing of the chatbot's support. Teams received chatbot assistance either in the first half or the second half of the decision-making task. In both scenarios, the chatbot sent three identical messages at two-minute intervals. The chatbot appeared as a participant in the Zoom conference, featuring a profile picture but no video or audio. It interacted with participants through chat messages. The chatbot's setup mimicked the integration of Zoom chatbots into the platform (Chaves and Gerosa, 2021). Following a common approach in human-AI interaction research (Sebo et al., 2020), we manipulated the chatbot using the Wizard-of-Oz method to ensure consistency. The second factor, *Information Distribution* (fully distributed vs. partially distributed), changed the allocation of task information among team members. As the manipulations were specific to the task performed by the teams, we will elaborate on the details of these manipulations while discussing the team task.

Participants

In total, 220 participants finished the study. We recruited them through two channels: the online participant platform Prolific (Palan and Schitter, 2018) and a campus subject pool comprising psychology undergraduates at a private US university. Participants from Prolific received a payment of $12 for completing the study, while those from the subject pool earned course credit. As the task had an objectively correct solution, all participants were eligible for a $15 bonus if they made the correct choice.

All participants completed the experiment online using the video conferencing platform Zoom. They were required to keep their cameras on during the team decision-making discussion session, reflecting the team collaboration patterns prevalent during and after the pandemic. Participants were randomly assigned to teams of four. Due to technical issues, such as unstable internet connections, during the team discussion task, we excluded 32 participants from 8 teams from our data. Consequently, our analysis included 47 teams and 188 participants. Among them, 101 were male, 86 were female, and 1 was non-binary. Ages ranged from 19 to 57, with an average of 24.6 and a median of 23. The participants' ethnicities included 10 Asian, 101 African American or Black, 47 White, and 23 from other backgrounds. Seven participants did not disclose their ethnicity. All participants primarily spoke English, with 96 being native speakers and 92 being non-native speakers.

Task and conditions

The task was a hidden-profile task, where the information required for the optimal decision was distributed among team members (Stasser and Titus, 1985). We utilized a new product development task, developed by Mell et al. (2014). In this task, the teams acted as consultants, recommending to their client, "Teasies," which new product they should produce for the upcoming season. The teams had to assess the profitability of five new energy drink products and rank them in terms of potential profits. The decision required a total of 25 information items about each product's research and development, production, marketing, legal issues, and finance. Each team member received an information packet containing 14 of the 25 information items. To make the best decision, team members needed to share information to obtain the full details about the new products. They had 10 minutes to read their information packet and 15 minutes to discuss and make a collective decision.

In this task, teams were assisted by a chatbot that shared three identical information items for the decision. Besides information sharing, the chatbot did not interact with the team members. The participating teams were explicitly informed that the chatbot would only share its analysis of the information packets and would not engage in further interaction.

Our first experimental factor, Chatbot Assistance, varied the timing of the chatbot's information sharing. In approximately half of the teams, the chatbot was introduced at the beginning of the team discussion, before members started interacting. Upon entry, the chatbot greeted the team and sent out the first message containing one information item. The other two information items were sent out every 2 minutes. In contrast, the remaining teams received chatbot assistance in the second half of the team discussion. For these teams, the chatbot was introduced at the midpoint of the discussion (7.5 minutes), greeting the team and sending out the first message. The other two messages were again sent out every two minutes. All teams received a halftime reminder at 7.5 minutes, ensuring consistent disruption of team discussions in both conditions around the midpoint. The messages they received from the chatbot were identical and in the same order.

Our second experimental factor, Information Distribution, manipulated the allocation of the 25 information items among team members. In the fully distributed condition, 11 unique pieces of information were distributed among three of the four team members (Figure 1). Additionally, 9 information items were distributed among three team members, while one team member had access to all of them. The three information items shared by the chatbot were unique to only one of the team members. Participants in both information conditions received an equal amount of information, with each team member possessing the same number of pieces. None of the participants reported that the given time was insufficient to review their information packets.

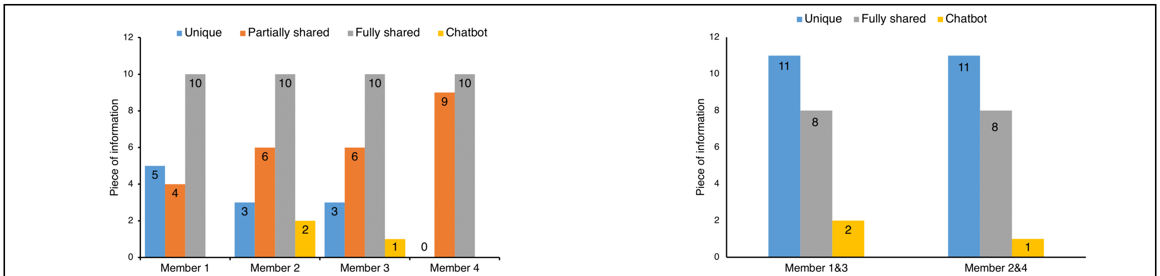


Figure 1: Information distribution among participants in both conditions. The left plot represents the fully distributed information. The right plot represents the partially distributed information.

In the partially distributed condition, two team members received identical information. The distribution of the 25 items was such that 8 items were shared by everyone, while each pair of team members had 11 unique pieces of information (Figure 1). The three items shared by the chatbot were unique to one of the pairs. In all conditions, each member received a total of 14 pieces of information and needed to share their information to obtain the full information and make the best decision.

Experimental Procedure

Upon entering the Zoom room, participants were greeted and randomly assigned to teams of four. Afterward, each team moved to its own breakout room session, where they were introduced to the task by an experimenter and signed an online consent form. Once all participants had signed the consent form, the experimenter began the Zoom recording. Participants then accessed their individual information packets and had 10 minutes to read them. The packets informed them that there was a correct ranking order among five product innovations and that members might have different information in their packets. During the individual reading session, participants were muted and could not talk to each other, and the Zoom chat function was disabled.

Next, the teams proceeded to the team discussion phase. They were allowed to keep and review the information packets during the discussion but were not permitted to show them to each other. They had 15 minutes to make a decision and were informed when half of the time had passed. The chatbot was introduced to a team either at the beginning or halfway through the team discussion. Before adding the chatbot to the video conference room, the experimenter explicitly informed participants that they would be assisted by a chatbot with access to information items, which would only share its analysis of these items. The chatbot shared the information through the chat with all team members while raising its hand in the interaction window. It shared the first piece of information along with its greeting message. To ensure participants knew where and how the chatbot shared the information, the experimenter asked them if they could see the chatbot's first message.

After 15 minutes, the experimenter ended the team discussion and asked the teams to provide a rank order of the products. Teams then proceeded to complete the post-experiment survey, which inquired about their perceptions of the chatbot, their teammates, and demographic information.

Measures

Cognitive Diversity

Various approaches to shared cognition (Carley, 1997; Wegner, 1987; Woolley et al., 2010) converge in the assumption that individuals possess latent knowledge structures in their minds, which are shared to varying extents among team members. Due to the challenges in gathering longitudinal data on group processes, previous studies have largely depended on self-reported measures to evaluate shared cognition in groups (Srivastava and Banaji, 2011). However, these measures exhibit limitations as they only supply static or sporadic information and may be subject to various reporting biases. Lix et al. (2022) suggested that by examining the language used by team members during their interactions, it is possible to obtain more nuanced and objective measures of cognitive diversity within a group, thereby addressing existing limitations and providing a more precise evaluation of collective cognition. In their computational model, they employed a word-embedding technique to encapsulate the context and semantic associations between words in a sentence. However, this approach encounters limitations when evaluating the communication, as word embeddings are incapable of conveying the overarching meaning of a sentence.

To account for word combinations, grammar, and sentence structure, enabling a more thorough understanding of the conveyed message, we developed a language-based tool for evaluating cognitive diversity. This was achieved by employing sentence embedding models, which are part of a family of unsupervised machine-learning methodologies that represent sentences in a high-dimensional vector space (Sutskever et al., 2014; Cho et al., 2014). We selected the publicly available Universal Sentence Encoder (USE) on TensorFlow-Hub for its ability to achieve consistently good performance across multiple NLP tasks (Cer et al., 2018), especially in analyzing team performance with embeddings (Enayet and Sukthankar, 2021). The model was trained on the Stanford Natural Language Interface (SNLI) corpus, Wikipedia, web question-answer pages, web news, and discussion forums. It outputs a 512-dimensional vector of text. As previously explained, the dimensions of an embedding space correspond to hidden features that underlie language use in the text. While these dimensions do not have meaningful interpretations, they are informative because sentences with similar meanings are positioned closer together in the space.

We converted the audio recordings of team interaction into texts using Amazon Transcribe. We manually corrected the inaccurately transcribed sentences. We then manually partitioned each team member's speech and concatenated each team member's text across the entire team discussion as well as for the first half and second half, respectively. The concatenated text was used as an input to USE (Cer et al., 2018) to obtain each team member's text vector representation in a given half of the team discussion and the entire discussion. We used normalized text vectors, in which the magnitude of the vectors was scaled to be equal to 1.

We calculated the cognitive diversity metric for every team for the entire team discussion and within the first and second half of the discussion. Let I be a team of N individuals, and W_{it} denote the concatenated spoken text expressed by the individual, i, during a time period, t, as derived from the individual's use of language during that time. We define the embedding distance between two individuals, *i* and *j*, during time *t*, as the cosine distance between their respective embedding:

$$d(W_{it}, W_{jt}) = 1 - cos(\overline{W}_{it}, \overline{W}_{jt}),$$

where cos(A, B) = $\frac{AB}{\|A\|\|B\|}$. Using this distance metric, we define a team's overall cognitive diversity as the average pairwise embedding distance between all team members.

$$CD_{It} = \frac{\sum_i^N \sum_j^N d(W_{it}, W_{jt})}{N^2}.$$

The process for calculating a team's cognitive diversity score is illustrated in Figure 1. First, we embedded each team member's concatenated sentences in a given time. Then, we computed the pairwise cosine distances between these person-vectors. Cosine similarity is particularly apt for high-dimensional data like text embeddings. It is an appropriate measure of similarity because it can capture the closeness in orientation regardless of their magnitudes. Finally, the team's cognitive diversity score was determined as the average of these pairwise distances.

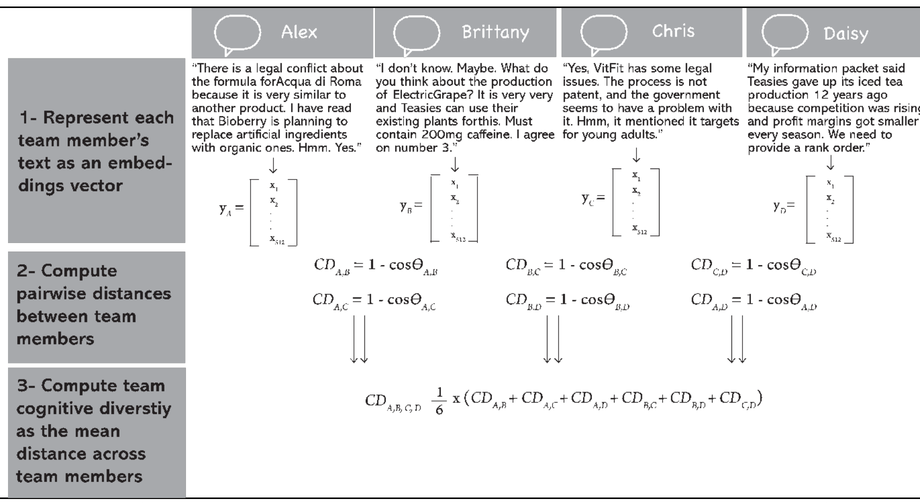


Figure 2: Steps for calculating the team cognitive diversity scores from the team discussion.

The diagram in Figure 2 provides an example of how team cognitive diversity scores are calculated at two halves of team discussion. The figure on the left side in Figure 3 represents the first half of team discussion when the team is more cognitively diverse. The figure on the right side in Figure 3 represents the second half of team discussion when the team is less cognitively diverse. In the first half of the team discussion, team members mention semantically different information, which results in their spoken words and sentences being located far apart in the embedding space. The pairwise cosine distances between the person vectors are large, which leads to a high cognitive diversity score for the team. In contrast, in the second stage, team members mention words and sentences that are more similar in meaning, causing the person-vectors to be located closer to each other in the embedding space. As a result, the cosine similarity distance between the person-vectors and the team's cognitive diversity score is lower.

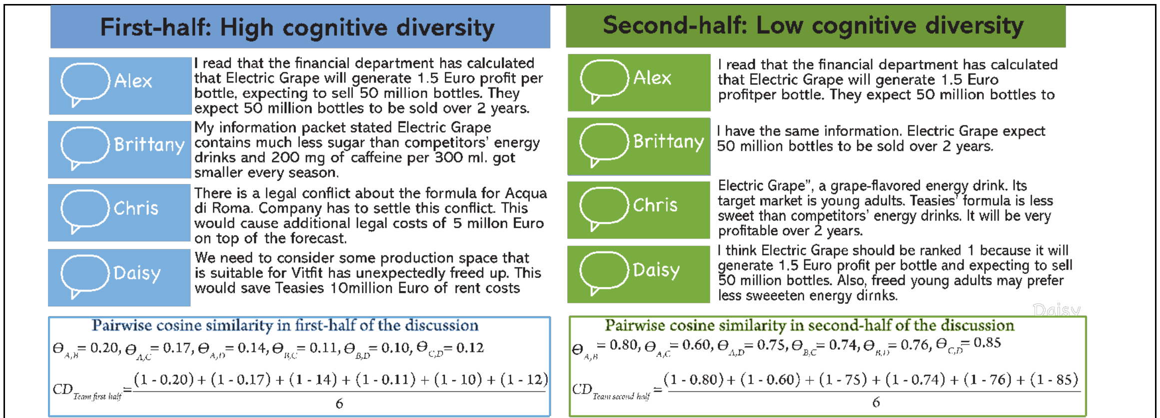


Figure 3: Diagrammatic example of high vs. low cognitive diversity scores

Information Elaboration

As described in Mell et al. (2014), the process of information elaboration was measured through a rating scheme. The rating scheme assigned a score from 0 to 5 to each item of information discussed, except for distractor items. To receive a score higher than 0, the item must have been mentioned during the discussion. If a team member concluded based on their information but did not recount the information items themselves and only shared the conclusion, those items were given a score of 0. The rating scale used to assess information elaboration consisted of five levels. A score of 1 was given when a team member mentioned an item, and a score of 2 was given when the item was acknowledged by at least one other team member or mentioned in response to a question but was not further discussed. A score of 3 was awarded when a team member asked a clarifying question about the mentioned item. A score of 4 was given when a conclusion was drawn from the item without explicitly integrating it with other information. A score of 5 was given when the item was combined with another piece of information. Items integrated by different people, or the same person received the same score of 5.

The team's information elaboration process was rated by two raters on the transcripts of team discussions. The two raters were unaware of the experimental conditions and assessed the same measures for 10 teams. The inter-rater reliability of the coding scheme was determined using intraclass correlations (ICCs). ICC1 referred to the reliability of a single rater, while ICC2 referred to the reliability of the averaged rating (Homan et al., 2007; Ten Velden et al., 2010). The inter-rater reliability for the raters was high (ICC1 0.85, ICC2 0.86).

Team performance

The team performance indicated the quality of their decisions and was derived from how closely their solutions matched the correct answer. For each group of choices, an objective ranking existed for the five product options. The quality of team decisions was measured by their performance score, based on how similar their rankings were to the objectively correct ranking. As explained by Mell et al. (2014), the team performance score was determined by calculating the deviation of a team's rank from the optimal rank position for each of the five product innovations. The sum of these five deviation scores gave an overall score ranging from 0 to 12. Deviation refers to the difference between the position of an item in the "offered ranking" and its position in the "objective ranking." To make the score easier to understand, the value was subtracted from 12, with higher scores indicating better performance. For instance, a perfect match to the objective ranking results in zero deviation, yielding a maximum score of 12 (12 - 0 = 12).

Results

Cognitive Diversity

To test **H1**, a 2 x 2 ANOVA was conducted to compare cognitive diversity levels across the four experimental conditions. The analysis revealed a significant main effect of chatbot assistance timing on a team's overall cognitive diversity, $F(1, 41) = 7.42$, $p < 0.01$. Teams supported by the chatbot during the first half of the discussion exhibited higher overall cognitive diversity ($M = 0.53$, $SD = 0.13$) than those assisted during the second half ($M = 0.43$, $SD = 0.09$). Information distribution did not significantly impact the team cognitive diversity score, $F(1, 41) = 0.93$, $p = 0.33$. These results suggest that teams receiving chatbot assistance in the first half shared more diverse information during team interactions than those supported in the second half, supporting **H1**.

To further examine the chatbot's impact on team cognitive diversity, we analyzed the effects of chatbot assistance and information distribution on cognitive diversity during the two halves of the discussion. A 2x2 ANOVA revealed a significant main effect of chatbot assistance timing on team cognitive diversity in the first half, $F(1, 41) = 9.52$, $p < .01$. Teams supported by the chatbot during the first half of the discussion exhibited higher first-half cognitive diversity ($M = .41$, $SD = .09$) than those assisted in the second half ($M = .30$, $SD = .12$). Information distribution and the interaction between the two experimental conditions had no significant effect on first-half cognitive diversity in teams, $F(1, 41) = .02$, $p =.87$; $F(1, 41) = .34$, $p = .55$.

A 2x2 ANOVA found no significant effect of chatbot assistance, information distribution, or their interaction on team cognitive diversity during the second half of the discussion. Collectively, these findings suggest that introducing chatbot support in the early stage of team decision-making significantly enhanced cognitive diversity at the beginning of the discussion. However, providing chatbot assistance during the later stage of team decision-making did not appear to be as effective.

Information Elaboration

To test **H2**, A two-way ANOVA was performed to analyze the effect of experimental conditions on information elaboration. We found a significant main effect of chatbot assistance ($F(1, 41) = 4.59$, $p < .05$) and information distribution on information elaboration ($F(1, 41) = 3.75$, $p < .05$). Teams assisted by the chatbot in the first half elaborated more information ($M = 59.2$, $SD =14.2$) than teams assisted by the chatbot in the second half ($M = 47.7$, $SD = 19.9$). Teams with fully distributed information elaborated more information ($M = 59$, $SD =17.1$) than teams with partially distributed information ($M = 47$, $SD =17$). The interaction between the two experimental conditions was not significant ($F(1, 41) = .19$, $p < .66$). Therefore, **H2** was supported.

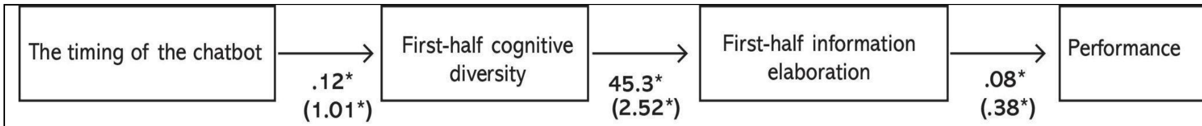
We also examined information elaboration during the two halves of the team discussion separately. A two-way ANOVA analysis showed a significant main effect of chatbot assistance on information elaboration in the first half ($F(1, 41) = 13.5$, $p < .001$) but no effect in the second half ($F(1, 41) = 0$, $p = .93$). Information distribution did not significantly influence information elaboration in either half of the team discussion ($F(1, 41) = 1.2$, $p = .27$; $F(1, 41) = 3.97$, $p = .06$). There were no significant interaction effects between the two conditions ($F(1, 41) = .63$, $p = .47$; $F(1, 41) = 2.05$, $p = .15$). In summary, the results suggest that the positive impact of chatbot assistance on information elaboration during the first half of team decision-making was primarily due to the increased engagement in the early stages of team discussion.

Team Performance

A 2 x 2 ANOVA was conducted to examine the impact of chatbot assistance timing and information distribution on team performance. The analysis showed a significant main effect of chatbot assistance timing on team performance, $F(1, 41) = 4.99$, $p = .03$. Teams that received chatbot support during the first half of the discussion performed significantly better ($M = 8.16$, $SD = 2.57$) than those assisted during the second half of the discussion ($M = 6.57$, $SD = 2.47$). Information distribution did not have a statistically significant effect on team performance, $F(1, 41) = 2.26$, $p = 0.13$. Nor was there an interaction effect of the two, $F(1, 41) = 0.19$, $p = 0.66$.

The Mediating Roles of Cognitive Diversity and Information Elaboration

H3 proposed that the effect of AI assistance timing on cognitive diversity predicts a) information elaboration and b) eventually, team performance in decision-making. To test them, we carried out multiple serial mediation analyses as recommended by Hayes (2013). We used cognitive diversity and information elaboration in the first half of the team discussion as mediators, since our previous analysis indicated that chatbot assistance had the most significant impact on these two variables. The results are visually represented in Figure 3 and summarized in Table 1.



Note: Path estimates are unstandardized regression coefficients, standardized regression coeffcients are in parantheses. * $p < .05$

Figure 3: Results of the Mediated Moderation Models

Predictor		*SE*[a]	*t*	R^2
Model 1: Team Performance				.14
Chatbot assistance (1=First half)	1.71	1.14	2.23*	
Information distribution (0 = Partially)	0	1.15	-.15	
Chatbot assistance X Information distribution	.69	.43		
Model 2: First half cognitive diversity				.19
Chatbot assistance (1=First-half)	.12	.04	2.69*	
Information distribution (0 = Partially)	.02	.04	.52	
Chatbot assistance Information distribution	.04	.07	.59	
Model 3: First half information elaboration				
Chatbot assistance (1=First half)	8.34	4	2	.40
Information distribution (0 = Partially)	-4.86	3.96	-1.22	
Chatbot assistance X Information distribution	3.39	5.71	0.59	
Cognitive diversity (0 = First half)	45.3	12.6	2.96**	
Model 4: Team Performance				.31
Chatbot assistance (1=First half)	.16	1.07	.15	
Information distribution (0 = Partially)	2.1	1.02	2.06	
Chatbot assistance X Information distribution	-1.27	1.45	-.87	
Cognitive diversity (0 = First half)	3.81	3.53	1.07	
Information elaboration(0 = First half)	0.08	0.04	2.14*	

[a]SE = standard error. * $p < .05$, ** $p < .01$.

Table 1: Regression Results for Serial Mediated Moderation Model

In the initial steps of the analysis, regressing team performance on the experimental conditions and their interaction reproduces the main effect of chatbot assistance timing discussed earlier. Regressing teams' cognitive diversity in the first half of the discussion on the experimental conditions and their interaction yielded the path coefficients for the first stage of the mediation model. The results showed a significant effect of chatbot timing on team cognitive diversity in the early stages of team discussion (β = .12, p < .05). Next, regressing information elaboration in the first half of the discussion on the conditions, their interaction, and the team's cognitive diversity in the first half of the discussion yielded the path coefficients for the second stage of the mediation model. The team's cognitive diversity in the first half of the discussion significantly predicted information elaboration in the first half of the discussion (β = 45.3, p < .05). Finally, regressing team performance on the complete series of predictors yielded the path coefficients for the last stage of the mediation model. In this model, information elaboration in the first half of the team discussion (β = .08, p < .05) significantly predicted team performance, while neither the chatbot timing nor cognitive diversity in the first half of the discussion showed any significant effect. Supporting **H3a and H3b**, the analysis revealed that the impact of chatbot assistance timing on team decision-making was mediated by cognitive diversity and subsequently by information elaboration.

Discussion and Conclusion

Our study investigates the potential for AI to improve team decision-making performance by influencing information-sharing processes within the team. Specifically, we examine the impact of introducing AI at various stages of team collaboration on cognitive diversity, information elaboration, and ultimately, the overall quality of decisions made. Results from an online experiment indicate that teams receiving chatbot assistance in the early stages of collaboration shaped the process of information sharing within the teams. Teams that were supported by a chatbot during the initial stages of the decision-making task exhibited higher levels of cognitive diversity and information elaboration, which in turn enhanced the quality of information sharing and decision-making outcomes. In summary, our findings suggest that AI assistance during team decision-making can offer both social and cognitive benefits for teams by promoting cognitive diversity and information elaboration. However, the timing of AI introduction is crucial.

Drawing on the notion that meaning is created collectively and dynamically through interaction (Berger and Luckmann 1967) and that communication among group members facilitates adjustments in understanding shared problems and potential solutions (Thompson and Fine 1999), we have developed a theoretical framework to elucidate the impact of cognitive diversity on team performance in hidden profile tasks. In this context, we introduce the concept of cognitive diversity—the variation in meanings expressed by group members during interactions. To develop novel measures of these constructs, we employed a deep-learning linguistic method (Cer et al., 2018) and data from a product development task. Unlike conventional survey-based approaches for assessing group cognition, our method enables the measurement of subtle temporal fluctuations in group members' cognitive diversity as they collaboratively adapt group cognition.

Our findings highlight the crucial role of temporality in determining AI's impact on teamwork. Although recent research has begun to explore AI's effects on teams (Jung and Hinds, 2018; Sebo et al., 2020; You and Robert, 2018), there is a limited body of theory and research on AI and team decision-making, even as its applications continue to grow. Furthermore, the temporal dynamics of team processes and their implications for human-AI collaboration remain under investigation. To address these gaps, our current study integrates theoretical perspectives from team research with emerging insights on human-AI collaboration. We demonstrate that the timing of AI introduction can lead to varied processes and outcomes in terms of team interaction, information sharing, and decision-making. By incorporating the temporal dimension into the study of human-AI collaboration, we aim to offer new theoretical insights into the role of AI in teams.

Our study, while providing valuable insights, has certain limitations which we highlight to inform future research and deepen the understanding of the topic. Firstly, the chatbot in our study was manipulated using the Wizard-of-Oz method. This approach was adopted to ensure consistency in our experimental manipulations and is in line with standard practices in human-AI interaction research (Sebo et al., 2020). However, it also implies that participants did not engage with a fully developed AI solution tailored for team decision-making. Future studies might consider using actual AI applications designed for teamwork to discern the effects of AI with immediate practical implications. In addition, future studies can examine whether the effect of a human teammate on the team information-sharing process would be the same as that of AI.

Another limitation arises from the study's experimental design. We recruited online participants for a lab experiment, and these individuals had not previously collaborated in an organizational setting. The strength of this sample lies in its ability to shed light on the effects of AI on newly formed teams, compared to teams with a longer collaboration history. Our findings suggest that the beneficial impact of AI on team decision-making can diminish, even when team members collaborate for only a short duration. Nonetheless, the selected sample could curtail the generalizability of our results, especially when considering organizational teams. Established teams in real-world settings might possess extensive task-specific knowledge and have established collaborative frameworks. To delve into the influence of established team norms and collaboration structures on AI's role, future research should focus on collecting data from such field teams.

Additionally, the timing of the chatbot's input plays a role in team information processes. A closer look at the effects of information shared both pre-and post the chatbot's message will enhance our comprehension of the chatbot's impact on the team's informational flow. We also segmented team discussions into two parts for assessing cognitive diversity. This approach may have overlooked the evolving nature of cognitive diversity throughout dialogues since team discussions can often be more aptly represented as a time series. Although our methodology presents an innovative way to measure cognitive diversity, eschewing reliance on self-reports, integrating other cognitive diversity metrics can lend credence to our new construct. Consequently, we advocate for future research to probe into alternate methodologies to acquire a richer understanding of team dynamics.

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