It depends on the timing: The ripple effect of AI on team decision-making

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Abstract

Whereas artificial intelligence (AI) is increasingly used to facilitate team decision-making, little is known about how the timing of AI assistance may impact team performance. The study investigates this question with an online experiment in which teams completed a new product development task with assistance from a chatbot. Information needed for making the decision was distributed among the team members. The chatbot shared information critical to the decision in either the first half or second half of team interaction. The results suggest that teams assisted by the chatbot in the first half of the decision-making task made better decisions than those assisted by the chatbot in the second half. Analysis of team member perceptions and interaction processes suggests that having a chatbot at the beginning of team interaction may have generated a ripple effect in the team that promoted information sharing among team members.

Keywords: artificial intelligence, chatbot, teams, decision-making, temporal dynamics

1. Introduction

Today's teams work in an environment characterized by ubiquitous computing supported by the Internet and artificial intelligence (e.g., machine learning algorithms, smartphones, and virtual assistants). Artificial intelligence (AI) refers to a generation of technologies that can perform cognitive functions like the human mind by gathering information from outside, analyzing the information to identify patterns or make predictions, and evaluating their own results to improve its decision rules (Russell and Norvig, 2009). AI has been increasingly deployed to assist human decision-making in a variety of different contexts (Malone, 2018), ranging from business and market decisions (Colson, 2019), military support and command decisions (Bisht et al., 2018) and medical diagnosis and treatment (Lebovitz et al., 2022).

AI has superior cognitive capacity and has clear potential to augment human cognition and team decisions (Fiore and Wiltshire, 2016; Ward, 2013). However, studying how AI influences team collaboration is challenging because teams are complex systems in which members and technologies interact through emergent and dynamic processes (Arrow et al., 2000). Although research on AI in teams is emerging (M. Jung and Hinds, 2018; Sebo et al., 2020; You and Robert, 2018), existing research still lacks coherent theoretical frameworks and has many unanswered questions (M. Jung and Hinds, 2018).

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, our study joins the budding research of human-AI teaming to examine how the application of intelligent agents may impact team decision-making depending on the timing of the technology assistance.

We focus on timing because the temporal stage in teams significantly shapes team processes (Tuckman and Jensen, 1977; Gersick, 1988; 1989) and will likely impact how teams adapt to a new intelligent technology, which in turn influences the effect of the technology on teams. We conducted an online experiment in which decision-making teams were assisted by a chatbot who shared critical information for team decisions either in the first or second half of their task. We found that the positive impact of chatbot assistance was stronger

URI: https://hdl.handle.net/10125/102667
978-0-9981331-6-4

if the agent was present in the first than the second half. Further analysis of team interaction processes indicated that the presence of the chatbot in the first half of the team decision-making task was more likely to generate a ripple effect among team members, thus facilitating information sharing and team decision quality. Our findings demonstrate the importance of temporality in understanding AI's impact on teams.

2. Related Research

Whereas early research on human-AI teaming focused on to what extent human members can trust and work with intelligent technologies to perform tasks (You and Robert, 2018), more recent research has started to examine how these new technologies may influence the interaction processes and dynamics among human members (Sebo et al., 2020). Text-based chatbots are one particularly interesting instance of such technologies since they have been suggested as team facilitators for task support (Avula et al., 2018; Toxtli et al., 2018).

However, the impact of intelligent agents on team processes and performance remains inconclusive. Compared to human facilitators, intelligent personal assistants facilitating team problem solving promoted equal participation, positive affect and creativity of group solutions, while increasing idle chats (Winkler et al., 2019). Intelligent technologies moderating team conflicts generated positive or negative impacts on members' affect and perception of conflict, depending upon conflict types (i.e., task vs. interpersonal conflicts) (M. F. Jung et al., 2015). The application of robots (i.e., surgical robots, pharmaceutical dispensing robots) in medical settings were observed to disrupt team interaction and coordination, and leading to reconfiguration of roles, status and knowledge specialization (Barrett et al., 2012; Sergeeva et al., 2020). When it comes to decision-making, virtual assistant tools can ease team decision making in large heterogeneous teams by incorporating cognitive mechanisms to enhance agreement and avoid bias (Pérez-Soler et al., 2018). Experimental work has shown that chatbots may promote discussions in social chat groups by encouraging reticent members to speak and organizing opinions have helped members contribute more evenly to the discussion, leading to improved satisfaction (Kim et al., 2020).

Despite the critical effect of temporal stage on team dynamics (Arrow et al., 2000; Mathieu and Zaccaro, 2001; Gersick, 1988; Tuckman and Jensen, 1977), little research has investigated the impact of temporality on AI's influence on teams. To fill this gap, the current research examines to what extent the timing of AI assistance influences team information sharing and performance in decision-making. The study builds on decades of research on team decision-making to offer theoretical insights on human-AI team collaboration. Introducing the temporal dimension to the research on human-AI teaming may also help scholars to find a theoretical perspective to explain the mixed findings on AI's impact on team collaboration and performance.

3. Theory and Hypothesis

Team decision-making is a major task routinely performed by teams in various contexts (Van Ginkel and Van Knippenberg, 2008). Decision-making in teams involves information sharing, elaboration, analysis, and, forming consensus (McGrath, 1984). Organizational teams often consist of members with different expertise and background, thus holding some unique information to contribute to team decisions. However, years of research on team decision-making has shown that when information needed for making decisions is distributed among team members, members tend to share common rather than unique information, resulting in insufficient information sharing, premature consensus, and sub-optimal decision outcomes (Lu et al., 2012; Stasser and Titus, 2003).

An AI may help overcome these challenges and support better team decision-making by 1) collecting and providing needed information, 2) facilitating team information sharing and elaboration, and 3) analyzing information and making recommendations (Colson, 2019; Yang et al., 2019). However, existing research suggests that the introduction of new intelligent technologies like AI may trigger changes in team processes, since technology adoption offers an opportunity for restructuring in teams (Barley, 1986). Because AI possesses strong cognitive abilities, it may impact how team members evaluate the expertise of their peers (Ward, 2013). The interactive features of AI can also sway the interaction patterns among team members (Lee et al., 2012;Strohkorb Sebo et al., 2018). Therefore, it is reasonable to propose that AI assistance may influence team information sharing and decision-making quality.

The timing of new technology assistance in teams is important in shaping team interaction and performance because where a team is in its life span impacts how the team members work together and how they will respond to the new technology. Teams are complex systems in which many interdependent members interact to achieve a collective goal (Arrow et al., 2000). Shared team structures emerge as the members interact over time, making the temporal dynamics a critical dimension in team processes. For example, compared to new teams, mature teams may have developed shared cognition, such as transactive memory systems, which facilitates member coordination but may or may not benefit teams' utilization of new technologies (Wegner, 1987; Yan et al., 2021). Research also shows that teams tend to experience a significant transition in interaction patterns at the temporal midpoint of task completion (Gersick, 1988; 1989). Around the midpoint, as members are aware of the time left before the end of the task, they tend to adjust their collaboration patterns in order to finish the task on time.

Given these temporal dynamics in teams, we predict that accessing a new intelligent agent in team decision-making will generate different impacts on team decision quality depending on its timing. A number of studies have reported a ripple effect of intelligent agents in social interaction – as the agents interacted with people in particular ways, people pick up the interaction style from the technological agents and interacted with their human counterparts in the same manner (Lee et al., 2012; Oliveira et al., 2018; Strohkorb Sebo et al., 2018). Therefore, if a new intelligent technology that offers information and analysis is introduced in teams, the information sharing behavior from the technology can serve as a social cue to encourage team members to share their information even when other members have not mentioned it – thus helping teams overcome the tendency to only share common rather than unique information.

When a team is just assembled, a newly introduced intelligent agent may generate a stronger influence on how members talk and interact with one another, since members are only starting to learn how to work together and probably haven't formed any shared norms or cognition. When information is shared by an AI in the teams, members may follow the technology and share information with one another. Unique information distributed among members is thus more likely to be thoroughly shared, which in turn enhances team performance. In contrast, if the agent begins its information sharing after the teams have worked on the task for a while, the team may have formed certain patterns or norms of collaboration. Thus it could be harder for the technology to restructure the existing interaction pattern in teams, making the technology less useful in promoting team information sharing and performance. We hereby propose:

H1: In decision-making, team performance is higher if the team is assisted by intelligent agents at the beginning of the team collaboration than in the later stages.

The pattern of information distribution among team members also matters since it can affect team interaction processes. Mell and colleagues (2014) found that if needed information from different knowledge areas (e.g., finance, marketing, production) is distributed among team members as opposed to being combined together, teams share less information and make worse decisions. This is because when information is highly distributed, each team member accesses a large body of unique information and may experience difficulty in understanding what others know and don't know. Consequently, much unique information won't be mentioned or cued by each other and may be left unintended as a result of social confirmation bias (Lu et al., 2012; Stasser and Titus, 2003). When the information is partially shared, however, more than one member may have similar information or opinions. Thus more overlapping information is likely to be mentioned by team members, attracting others with similar information to elaborate on it and convincing the team to consider the information in their decision. As a result, more information will be shared and used in partially distributed information contexts, which in turn improves team decision-making quality.

We thus predict that having AI assistance at the beginning of the team collaboration (vs. later stages) will enhance team decision quality even more when information is less distributed among team members. When information is at least partially shared, information sharing from an intelligent agent is more likely to lead to information sharing from team members. Once shared information is mentioned by both the technology and one more team member, it may further attract other members with the same information to join the discussion, creating a situation in which a minority or majority of the team is endorsing the same information and enhancing the influence of the information on the rest of the team (Nemeth, 1986). Therefore, more information is likely to be shared, elaborated and considered by the team in their decision-making process, which eventually supports the team to make better decisions.

H2: In decision-making, the effect of the timing of intelligent agent assistance on team performance depends on the information distribution among team members, such that the positive impact of early intelligent assistance is stronger when information is partially than fully distributed.

4. Methods

We conducted an online experiment to test our hypotheses. In the experiment, teams of four participants performed a decision-making task together. The decision-making task was a hidden-profile task in which the information needed to make the best decision was distributed among team members (Stasser and Titus, 1985; Mell et al., 2014).

The experiment followed a 2 $\times$ 2 between-subject factorial design (N = 47). The first factor, *Chatbot Assistance* (first-half vs. second-half), manipulated the timing of chatbot assistance. Teams either received chatbot assistance in the first half of the team decision-making task or the second half of the task. In both conditions, the chatbot sent out 3 identical messages in a two-minute interval. The second factor, *Information distribution* (fully distributed vs. partially distributed), varied the distribution of task information among team members. Since the manipulations concerned the specific task the teams performed, we will discuss the details of the manipulations when explaining the team task.

4.1. Participants

A total of 220 participants completed the study. The participants were recruited through two sources: the online subject platform Prolific (Palan and Schitter, 2018) and a campus subject pool consisting of undergrads of psychology in a private US university. Participants recruited in Prolific receive a payment of 12 US dollars for completing the study. Subject pool participants received course credit. Since the task has an objectively correct answer, all participants were offered a 15 US dollar bonus if they made the correct choice.

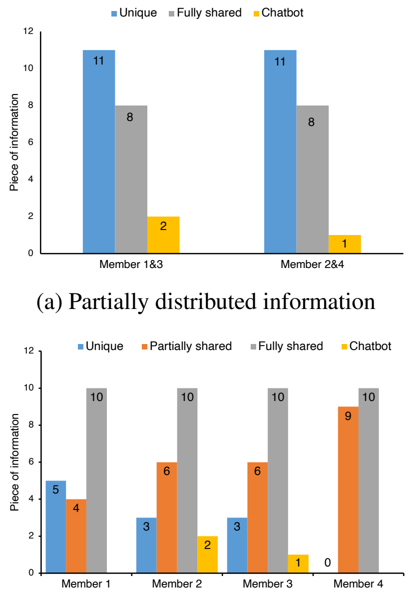
All participants completed the experiment online via the video conferencing platform Zoom. They were required to keep their camera on during the team decision discussion session. This design mimics the team collaboration pattern prevalent during and after the pandemic. Participants were randomly assigned into teams of four. Due to the technical problems (e.g., unstable Internet connection) during the team discussion task, we excluded 32 participants in 8 teams from our data. This results in 47 teams and 188 participants in the analysis. Among them, 101 were male, 86 were female, and 1 was non-binary. Their ages ranged from 19 to 57 with a mean of 24.6 and a median of 23. There were 10 Asian, 101 African American or Black, 47 White, and 23 other. The remaining 7 did not disclose their ethnicity. English was the primary language for all participants. 96 were native speakers of English and 92 were non-native speakers.

4.2. Task and Conditions

The decision-making task we used was a new product development task developed by Mell et al. (2014). In this task, the teams took the role of a team of consultants and made recommendations to their client, ”Teasies”, regarding which new product they should produce for the next season. The teams collectively assessed the profitability of five new energy drink products and rank-ordered the products in terms of potential profits. The complete information needed to make the decision consisted of 25 information items regarding each product’s research and development, production, marketing, legal issues, and finance. Each team member received an information packet that included 14 out of the 25 information items. Therefore, to make the best decision, team members need to share information with each other to obtain the full information regarding the new products. For the task, team members had 10 minutes to read their own information packet and 15 minutes to discuss and make a collective decision.

In the task, teams were assisted by a chatbot that shared three information items critical for the decision. These information items were pre-determined by the researchers and were identical across all conditions. Our chatbot had a simple cognitive function that is to share critical items with other team members in a time interval to support team decision. Information sharing is a critical cognitive process for team collaboration because team members can only understand each other and work together by sharing information (Hinsz et al., 1997). Other than information sharing, it did not interact with other team members. Team members were explicitly told that the chatbot would only share its analysis of the information packets and would not interact with them.

Our first experimental factor, *Chatbot Assistance*, varied the timing of the chatbot information sharing. In about half of the teams, the chatbot was introduced at the beginning of the team discussion before team members started to interact. Upon entry, the chatbot greeted the team and sent out the first message containing one information item. The other two information items were then sent out every 2 minutes. In contrast, the other half of the teams received the chatbot assistance in the second half of the team discussion. For these teams, the chatbot was introduced at the mid-point of the discussion (7 and a half minutes), greeting the team and sending out the first message. The rest two messages were again sent out every two minutes. All teams received a half-time reminder at 7 and a half minutes so it was consistent that team discussions in both conditions were disrupted around the mid-point.



(a) Partially distributed information

(b) Fully distributed information

Figure 1: Information distribution among team members in both conditions.

The messages they received from the chatbot were identical and in the same order.

Our second experimental factor, *Information Distribution*, manipulated how the 25 information items were distributed among team members. In the fully distributed condition (Fig. 1b), 11 unique pieces of information were distributed among the team members. Another 9 information items were shared by 2-3 members, and 10 information items were known to everyone. The three information items shared by the chatbot were the unique information items belonging to only one of the team members. Participants in both information conditions received the same amount of information. Each team member had an equal number of information pieces. No participants reported that the given time was not enough for them to review the information packets.

In the partially distributed condition (Fig. 1a), two team members received the same information. The information distribution of 25 items was such that 8 information items were shared by everyone, and each pair of team members had 11 pieces of unique information items. The three information items shared by the chatbot were the unique information items belonging to one of the pairs. In both condition, all members need to share their information in order to make the best decision.

4.3. Experimental Procedure

When participants entered the Zoom room, they were greeted and randomly assigned into teams of four. After the assignment, each team entered their own breakout room session, they were introduced to the task by an experimenter and signed a consent form online.

After the consent form was signed by all participants, the experimenter started the recording in Zoom. The participants then accessed their individual information packet and had 10 minutes to read it. The information packet told them that there was a correct ranking order among five product innovations and members might have different information in their information packets. The participants were muted and could not talk to each other during the individual reading session. The chat function in Zoom was disabled for the participants.

Next, the teams continued with the team discussion phase. They were allowed to keep and review the information packets during the discussion but not to show them to each other. They had 15 minutes to make a decision and were informed when half of the time is spent. The chatbot was introduced to a team at the beginning or half of the team discussion. Before the chatbot was added to the video conference room, the experimenter explicitly told participants that they would be assisted by a chatbot that had access to information items and that the chatbot 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. The chatbot shared the first information along with its greeting message. To ensure participants know where and how the chatbot shares the information, the experimenter asked participants whether they were able to see the first message by the chatbot.

After 15 minutes, the experimenter stopped the team discussion and asked the teams to offer a rank order of the products. Teams then proceeded to complete the post-experiment survey, which asked about their perception of the chatbot, their teammates and the demographics.

4.4. Measures

4.4.1. Dependent Variable: Team Performance

As described in Mell et al. (2014), team performance score was considered as the quality of teams' decisions. It was calculated based on the similarity of their rankings to the objectively correct ranking. We first calculated the deviation of the rank a team gave from the optimal rank position. We then summed these five deviation scores into an overall score that ranged from 0 to 12. For ease of interpretation, we subtracted this value from 12, which yielded a performance score with higher values indicating better performance.

4.4.2. Team Discussion Process In order to analyze team discussion processes, we converted the recorded team discussion to texts using Amazon Transcribe. The transcribed texts were analyzed using automated text analysis software Linguistic Inquiry and Word Count (LIWC) (Pennebaker et al., 2015). The tool is applied to the measurement of a wide variety of constructs (for a review, see Tausczik and Pennebaker, 2010).

In our study, we rely on the LIWC measure, *Analytical Thinking*, to investigate the extent to which members engaged in information sharing and analysis. Analytical thinking is a summary variable generated by LIWC, indicating the level of logical and structured thinking in the communication (Pennebaker et al., 2014). The measure is a standardized score ranging from 1 to 99, with a higher score indicating that a higher degree of logical analysis is reflected in the texts. Thus high analytical thinking in team discussion can indicate high levels of information sharing and elaboration. Since our manipulation of chatbot assistance was either in the first or second half of the team interaction process, we also separated the transcribed team interaction into two halves and calculated their corresponding analytical thinking scores.

4.4.3. Perceived Information Value We also measured the perceived information value from the *chatbot* and *team members* in order to understand to what extent team members considered information offered by the chatbot and their peers. The items were as follows: 1) "How valuable did you think the information provided by the chatbot was for the task?", and 2) "How would you rate the value of the information provided by your teammates in the decision-making procedure, when compared to the information offered by the chatbot?". Each item was rated on a 5-point scale ranging from 1 to 5. Descriptive statistics and correlation matrix among major variables are summarized in Table 1.

5. Results

A two-way ANOVA was performed to analyze the effect of chatbot assistance timing and information distribution on teams' performance. Supporting **H1**, the analysis revealed a significant main effect of chatbot assistance timing on team performance, $F(1, 43) = 38.06$, $p = .01$. Teams assisted by the chatbot in the first-half of the discussion performed significantly better than the teams assisted by the chatbot (M = 8.24, SD = 2.6) in the second-half of the discussion (M = 6.54, SD = 2.4). Information distribution did not have a statistically significant effect on the team performance, $F(1, 43) = 2.52, p = 0.11$.

H2 predicted an interaction effect of chatbot assistance timing and information distribution such that having chatbot assistance in the initial stages would have a stronger effect when information was partially distributed. We found that the patterns of team performance across the four experimental conditions were consistent with the hypothesized interaction effect: as shown in Fig. 2, teams assisted by the chatbot in the first half had higher average performance when the information was partially distributed (M = 9.2, SD = 1.6) than fully distributed (M = 7.6, SD = 2.9). However, having chatbot assistance in the second half did not make much difference for teams (Partially distributed: M = 6.9, SD = 2.2; Fully distributed: M = 6.1, SD = 2.7). However, the interaction effect of chatbot assistance timing and information distribution was not significant. Thus **H2** was not supported, $F(1, 43) = 0.34$, $p = .56$. Taken together, our results showed that having chatbot assistance in the first-half of team discussion improved team performance more than accessing the chatbot in the second half. The effect persisted regardless of the information distribution within the teams.

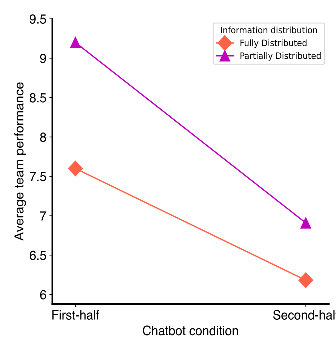


Figure 2: Team performance in experimental conditions.

5.1. Team Discussion Process

To probe the mechanism underlying the main effect of chatbot assistance timing, we analyzed the team discussion processes. The chatbot assistance at different times of the team discussion might have had distinct impacts on the teams' information sharing processes. A 2×2 ANOVA was performed to compare the level of *Analytical Thinking* in the four experimental conditions.

Table 1: Descriptive statistics and correlation matrix of major variables

Variable	Mean	SD	1	2	3	4	5	6
1. Chatbot assistance	0.53	0.5	1					
2. Information distribution	0.55	0.5	0.1	1				
3. Performance	7.45	2.66	0.32	-0.19	1			
4. Analytic thinking	26.75	8.63	0.21	0.03	0.12	1		
5. Information value of chatbot	4.14	0.56	-0.18	-0.11	0.27	0.04	1	
6. Information value of teammates	4.04	0.51	0.33	-0.05	0.07	-0.04	-0.26	1

Although in general, teams assisted by the chatbot in the first half had a higher overall analytical thinking score (*M* = 28.9, *SD* = 10.7) than those assisted in the second half (*M* = 25.5, *SD* = 10.7) throughout the discussion, we did not find any significant main or interaction effect of our manipulations on the teams' overall analytical thinking level (Chatbot assistance: $p = 0.17$; information distribution: $p = 0.95$; interaction effect: $p = 0.93$).

However, when comparing the *Analytical Thinking* level in the first and second halves of team interaction, we found that in first-half of team interaction, teams assisted by the chatbot (*M* = 30.3, *SD* = 11.6) demonstrated significantly higher levels of analytical thinking than those not assisted by the chatbot (*M* = 22.6, *SD* = 9.6), $F(1, 43) = 5.6, p = .0.02$) (Fig. 3). Team information distribution had no effect on the level of analytical thinking, $F(1, 43) = .02, p = .0.87$. There was also no interaction effect of the two factors, $F(1, 43) = .29, p = .0.59$. We did not find any significant main or interaction effect on the *Analytical Thinking* levels in the second half of team interaction (Chatbot assistance: $p = 0.81$; information distribution: $p = 0.48$; interaction effect: $p = 0.54$). In sum, the findings offered some evidence that teams assisted by the chatbot in the first-half started engaging in information sharing and analytical thinking early in the team interaction, the effect even carried on to the later stages of team collaboration, when the chatbot was no longer present.

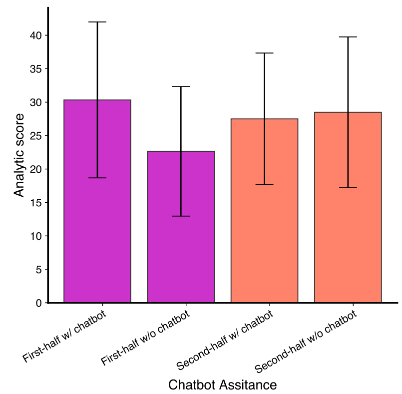


Figure 3: Analytical thinking in first and second half of team collaboration with and without chatbot assistance.

5.2. Perceived Information Value

A two-way ANOVA was first performed to analyze the effect of chatbot assistance and information distribution on team members' *perceived value of information from the chatbot*. We did not find any significant main or interaction effect of our manipulations on information value from the chatbot (Chatbot assistance: $p = 0.25$; information distribution: $p = 0.51$; interaction effect: $p = 0.14$). The non-significant results suggest that teams perceived the chatbot as equally valuable regardless of the timing of chatbot assistance.

Interestingly, the analysis showed that the timing of chatbot assistance significantly influenced members' evaluation of the value of information provided by their *teammates*, $F(1, 43) = 5.69$, $p = .02$. Teams assisted by the chatbot in the first-half of the discussion valued the information provided by their teammates (*M* = 4.2, *SD* = 0.5) more than teams assisted by the chatbot in the second-half (*M* = 3.8, *SD* = 0.4). Information distribution did not have a statistically significant effect, $F(1, 43) = 0.36, p = .55$. Nor was there an interaction effect, $F(1, 43) = 0.39$, $p = .53$. These findings together suggest that the timing of chatbot assistance may have improved team decision quality because it generated a ripple effect among team members: having a chatbot at the initial stages of team collaboration may have cultivated a team climate in which members' information was valued and carefully considered.

6. Discussion

The current study examined the impact of AI assistance timing on team decision-making. Through an online experiment, we found that teams assisted by a chatbot at the beginning of team collaboration made better decisions than those assisted by the chatbot in the later stage. Further analysis of team interaction processes showed that having AI assistance when the team just started to work together promoted team information sharing more than having the technology later. Team members' evaluation of peer information value revealed that having chatbot assistance in the initial stages seemed to have generated a ripple effect that facilitated information sharing and discussion among team members: when teams received chatbot assistance at early stages (vs at later stages), they evaluated peer information to be more valuable, suggesting that they considered and used each others' information more thoroughly in decision-making.

Our findings demonstrate the critical impact of temporality on AI's influence on teamwork. While recent research has started to examine the effect of AI on teams (M. Jung and Hinds, 2018; Sebo et al., 2020; You and Robert, 2018), little theory and research exists on AI and team decision-making despite the increasing applications. The temporal dynamics in team processes and their implications on human-AI teaming are also under-studied. The current study takes a step forward by integrating the theoretical perspectives in team research with emerging research on human-AI team collaboration. We show that the timing of AI introduction can generate different impacts on teams' interaction, information sharing, and decision making. By introducing the temporal dimension in the study of human-AI teaming, we seek to reconcile the mixed findings in extant literature regarding the impact of AI on team collaboration and provide new theoretical insights on AI in teams.

The study also generates important practical implications. It shows that organizations should carefully consider the timing when introducing a new AI technology to assist team decision-making. Introducing AI to assist teamwork can be more effective when the team is newly assembled for a task compared to after the team has worked together on a task for a while. When an AI has to be adopted in an established team, however, training may be needed to help teams adopt the new technology to make the application more helpful for team performance.

Our study is not without limitations. First, the study is a lab experiment that recruited online participants who never worked together in an organization. The advantage of this sample is that it offers us insights regarding the impact of AI in newly assembled teams compared to teams who have worked together for a while. We show that AI's positive effect on team decision-making can diminish even after team members only collaborated for a relatively short period of time. However, the sample may limit the generalizability of our findings to organizational teams since field teams who have worked together may have accumulated high levels of task-specific expertise and developed shared structures for collaboration. Future research should collect data from field teams to further explicate the mechanisms of existing team norms and collaboration structures on AI's impact on teams. In addition, the current study did not include conditions in which humans members share information at different time points, because it primary concerns how the timing of AI introduction may impact teams. Future research should consider adding the human condition to compare and explore the differences between human and AI's timing of information sharing to better understand the effects of AI.

Second, whereas English was the primary language for all participants, about half of our participants were non-native English speakers. This sample is not typical in studies that often focus on North American population, and may raise the question that to what extent team discussion and decision are affected by the language composition. On the other hand, the sample composition may enhance the external validity of our study because teams in large companies have both native and non-native speakers who are required to make decisions together. In addition, all participants were required to keep their camera on during the team discussion. Tomprou et al. (2021) found that team without visual cues are more successful in synchronizing their vocal cues and speaking turns. With virtual meetings become increasingly common, future studies can investigate the necessity of video support in diverse teams with a chatbot assistance.

Third, the chatbot was manipulated using the Wizard-of-Oz method. We chose this method to ensure the consistency of our experimental manipulations and because it is common in human-AI interaction research (Sebo et al., 2020). But this also means that the participants did not interact with an AI application that is already developed and applied in team decision-making. Future studies can examine existing AI applications for teamwork and adopt them to investigate the effect of AI for more straightforward practical implications. Lastly, we did not directly examine or compare the information sharing behavior and perception in teams when they were supported by the AI in the first versus second half of the team collaboration. Our measure of perceived information value gauged the relative value of information shared by members when compared to that shared by the chatbot, but did not directly evaluate the perceived value of member information. Our next step is to analyze the team interaction process and understand how and what information was shared by team members to explain the mechanism of the AI's effect on team decision-making. In future studies, we will also improve our measures of perceived information value to directly capture the perceived information value of human members.

Acknowledgement

This research was supported by National Science Foundation Grant 2105169.

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