A Mixed Methods Approach to Analyzing the Role of AI Teammates in Transition Phases

BEAU G. SCHELBLE, The University of Tennessee, USA
ROHIT MALLICK, University of Maryland, USA
NATHAN MCNEESE, Clemson University, USA

Recent innovations in AI have allowed AI agents to work as collaborative teammates; however, these human-AI teams still face significant challenges in achieving high levels of effective coordination and collaboration. Focusing on the temporal nature of teaming, collaboration is often evaluated and improved through transition-phase discussions, held among teammates before or after achieving team goals. Using a mixed-methods approach, this study examines how AI teammates participate in transition-phase discussions and share various types of information, with a focus on situation awareness, impact on team cognition, trust, and performance in human-AI teams. Data from 31 teams completing a three-hour simulated uncrewed aerial system task, comprising four distinct rounds and two transition phases, were analyzed. Quantitative results indicated that AI involvement later in the team's life cycle fostered more trust in the AI teammate, as compared across the four rounds, and was associated with higher performance. Perceived team effectiveness also improved following transition phases the AI teammate participated in, irrespective of whether it occurred early or late in the team's life cycle. Qualitative findings revealed that AI involvement benefits transition phases, particularly when it prompts teammates to recall task details and develop shared knowledge. Based on these results, we demonstrate the value of AI teammates engaging in transition-phase discussions for human-AI teams and provide design recommendations for researchers and practitioners to improve the efficacy of HATs by implementing transition phases.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; **Empirical studies in HCI**;

Additional Key Words and Phrases: Human-AI Teams, Communication, Transition Phases, Autonomy, Artificial Intelligence, Trust, Situation Awareness

ACM Reference Format:
Beau G. Schelble, Rohit Mallick, and Nathan McNeese. 2026. A Mixed Methods Approach to Analyzing the Role of AI Teammates in Transition Phases. *Proc. ACM Hum.-Comput. Interact.* 10, 1, Article GROUP003 (March 2026), 26 pages. https://doi.org/10.1145/3799438

1 Introduction

AI-enabled systems are making meaningful contributions as members of collaborative entities known as human-AI teams (HATs), which past literature has shown can outperform human-only teams, leading to their deployment in real-world settings [14, 46, 61]. However, HAT performance frequently struggles when high levels of complex communication, coordination, and other abstract interaction patterns are necessary [18, 23]. As such, these interactive AI systems pose significant design challenges, necessitating research to understand how AI teammates should be designed to

Authors' Contact Information: Beau G. Schelble, bschelbl@utk.edu, Industrial & Systems Engineering, The University of Tennessee, Knoxville, TN, USA; Rohit Mallick, mallick@umd.edu, College of Information, University of Maryland, College Park, MD, USA; Nathan McNeese, Human-Centered Computing, Clemson University, Clemson, SC, USA, mcneese@clemson.edu.

ACM 2573-0142/2026/3-ARTGROUP003
https://doi.org/10.1145/3799438

support more involved collaboration. One component of successful teams that enables complex collaboration on tasks is the transition phase, which provides teams with the opportunity to discuss plans, roles, goals, and strategies to improve upon past performance [22, 40]. These transition phases enable teams to enhance a range of critical team constructs, including trust, information sharing, team cognition, and ultimately performance [40]. Unfortunately, there is a limited understanding of how or when AI teammates should be designed to engage in these transition phases, especially regarding how they should share information before, during, and after these phases [54].

Developing AI teammates capable of effectively participating in team transition phases is crucial to realizing the true potential of HATs. Effective team transition phases have a long, positive, and replicable effect on teaming performance [40, 73] and on the development of team cognition [74]. The reason for this effect is clarified by the definition of transition phases, which refers to any period during which a team is not actively working toward its shared goal (e.g., downtime between missions, formal team briefings, or debriefings). In these transition phases, team members will discuss past performance, goal specification, and strategy formulation [19, 40, 56]. Typically, AI teammates are not part of this conversation, which is detrimental, as these transition-phase discussions will inevitably include their actions, shortcomings, and strengths, as well as how to work with or around them. As such, AI teammates miss out on what objectives to prioritize, what information to share and when, and how to improve their teamwork behaviors [40]. The existing literature on AI participation in transition phases is virtually non-existent [54], making it unclear whether the timing of an AI teammate's involvement in these transition-phase discussions is beneficial, harmful, or irrelevant, depending on the team's stage in its development life cycle.

AI teammates engage in teamwork primarily by sharing relevant information, which underpins the development of strong team cognition through shared mental models (SMMs) and situation awareness (SA). Team cognition is an emergent state of teams encompassing many team-level cognitive constructs related to team effectiveness, with team SA [3] and SMMs [7] being typical examples. These constructs depend on effective information sharing among teammates, whether artificial or otherwise [7, 13]. However, AI teammates occupy a unique position for information sharing, given their numerous technical advantages [10]. For example, AI teammates could augment team memory by serving as repositories for vast amounts of task- and team-related information, in addition to their individual taskwork duties. Transition phases provide a natural medium for sharing, evaluating, critiquing, and planning with this AI information-sharing, thereby enabling human-directed adaptations of AI teammate behavior and further empowering AI design toward human-centered design principles. Still, many questions about how information-sharing can directly contribute to team cognition remain unexplored in HATs, limiting their ability to move beyond utility in taskwork to utility in teamwork.

Therefore, it is vital to enhance our understanding of how AI participation in transition phases and its interaction with AI information-sharing affect HAT performance and the development of team cognition and trust. These research gaps are encompassed by the following research questions, which the current study addresses:

RQ1: *What effect does AI teammate participation in transition phases have on human-AI teams?*

RQ1.1: Regarding trust?

RQ1.2: Regarding perceived shared mental models?

RQ1.3: Regarding team performance?

RQ2: *How does the effect of AI teammate participation in transition phases change if it occurs earlier versus later in the team's life cycle?*

RQ3: *What effect does the type of information shared by an AI teammate have on the interaction teams have with them throughout the teaming life cycle?*

Utilizing a mixed-methods approach, the current study addressed these RQs by examining teams completing a complex simulated flight task alongside an AI teammate that participated in a transition phase early or late in the team's life cycle, and had one of three information-sharing attributes. The results of this design led to several key takeaways: AI teammates participating in the transition phase later in the team's life cycle produced more consistent trust in the AI teammate and led to higher objective performance. Still, the AI teammate's mere involvement in the transition phase led to greater perceived team performance immediately afterward, regardless of when it occurred. Participants qualitatively reported that AI involvement benefited their transition phases, particularly through the AI teammate's ability to support the development of task knowledge simultaneously with all teammates, thus enhancing shared knowledge. Therefore, it is clear that AI participation in the transition phase significantly affects perceptions *and* performance within HATs, and these effects vary with the timing and manner of the AI teammate's interaction. Such a finding should serve as a clear call to action for those studying HATs, as there remains much to understand about the role of AI that participates in the *full* cycle of teaming. This work contributes to the fields of computer-supported cooperative work (CSCW), human factors (HF), and human-computer interaction (HCI) by being one of the first empirical studies to examine the impact of AI participation in transition phases for HATs, a critical aspect of teaming essential for understanding and implementing the design of effective collaborative AI. Lastly, the work builds on prior research on AI information-sharing in decision-making and teaming, explicitly examining the effects of AI transition-phase participation and the moderating effect of AI information-sharing on team constructs.

2 Background

The following background section reviews relevant research focusing on supporting teamwork in HATs through team cognition and the life cycle of teamwork within CSCW. These topics outline the research gaps that motivate the current study on AI participation in transition phases and information sharing.

2.1 Supporting Effective Human-AI Teamwork through Team Cognition

Within HCI, HF, and CSCW, HATs are defined as teams comprising at least one human and one artificial agent, with significant agency in decision-making, that collaborate interdependently to accomplish a shared goal [50, 54, 62]. By incorporating principles of teamwork, HAT continues to advance the literature on autonomous system design by exploring how AI can be further tuned to support collaborative task success and align with human teammates' expectations [63]. Previous literature in the HCI space has noted that these artificial agents can provide numerous benefits to collaborative work, given their innate technical advantages, including the ability to process large amounts of data quickly, greater resilience towards fatigue, and consistency [67, 70]. Despite these advantages, humans still outperform AI when operating under conditions of uncertainty and incomplete information, as humans can ascertain the underlying meaning behind information to improve decision-making [4, 34, 70]. Consequently, AI teammates must perform many tasks without the constant oversight of their human teammates, requiring AI teammates to be trustworthy agents capable of building and fostering appropriate trust with their human teammates to ensure their proper acceptance and usage [15, 22, 38, 54]. As such, the design of HATs and their supporting systems leverages the inherent strengths of AI and humans to complement one another and achieve outcomes greater than either could achieve alone [30, 47].

A critical component of collaborative work, team cognition and trust significantly influence team effectiveness in completing complex, interdependent tasks [7, 32, 42]. Within the context of HATs, trust is often defined as one party's willingness to become vulnerable to the actions of another party [44]. Team cognition is a related concept in teaming, comprising the collective cognition within teams that encompasses SMMs, SA, and an attitudinal understanding of one another's beliefs, emotional states, and cognitive workloads [1, 11, 62]. Focusing explicitly on SMMs and SA, SMMs represent formalized shared knowledge across team members [7], while SA represents a three tiered operationalization of individuals real-time understanding of objects within their environment (Level 1 SA), their meaning within the environment (Level 2 SA), and their projected status in the near future (Level 3) [21]. HATs frequently struggle to develop effective team cognition [22], as studies show poor communication within HATs as they often fail to anticipate information needs, which then increases information requests and communication overhead [16, 18]. These HAT shortcomings stem from the strong relationship between team cognition and team performance [22, 42, 49]. Ultimately, to effectively develop, refine, and support team cognition, teammates must exchange critical information when necessary and engage in meaningful active discussions [17, 60, 75]. Engaging in these discussions and supporting improved information-sharing in HATs will require CSCW to accommodate the full life cycle of teaming, explicitly designing collaborative systems to engage with team transition phases.

2.2 Developing for the Life Cycle of Teaming in CSCW

CSCW research on HAT has yet to leverage the full life cycle of teaming to enhance the design of collaborative technologies, thereby improving team cognition, performance, and trust within these teams. For instance, while the temporally based framework of team effectiveness by Marks and colleagues has been cited in the literature, a core component, the breakdown of the team life cycle into action and transition phases [40], has not yet been effectively integrated into HAT studies [54]. This framework distinguishes two primary phases in teaming: 1) the "action" phase, defined as any time a team is actively working toward achieving its shared goals [40]; 2) the "transition" phase, which is defined as any time where teams are not actively working towards that shared goal but do engage in planning, strategy development, goal definition, and evaluation of past performance [40]. These transition phases enable teams to communicate extraneous information that cannot be shared or evaluated during the pressures of an action phase, but do improve SMMs, SA, team affect, trust, and several other relevant team constructs [1, 20, 40]. Both stages are essential for teams to perform the task well and ensure that performance is sustained, if not improved, for future occurrences.

In this way, the temporal framework of team effectiveness is a flexible model in aligning teammate behavior, a fundamental perspective of team cognition [40]. Developing collaborative AI systems to integrate into and participate in these transition phases effectively is crucial, especially as the CSCW field addresses "black box" decision-making in AI systems, where it is uncertain how information was elicited and evaluated to inform AI actions [59]. Concepts such as explainability and transparency have been introduced into the design of collaborative AI systems to explicitly enhance shared understanding and awareness [8, 22]. Transition phases represent a natural and optimal medium for AI teammates to actively engage in these actions. Furthermore, although AI teammates lack the same mental representations and information organization as humans, such as SMMs and other latent constructs, they may still contribute to improving these characteristics within their team through their information-sharing capabilities. An existing study investigating the pivotal role of social support in CSCW contexts, such as eSports, found that informational support among teammates often led to emotional and esteem-based affective social support, thereby enhancing existing relationships [26]. However, the amount of information provided and when it is provided throughout the mission's life cycle have not been explored and are the focus of the current study. The current research aims to bridge these gaps by understanding how human teammate react and prefer the information-sharing capabilities of their AI teammates.

These larger research gaps motivating the previously detailed RQs highlight how much more expansive the role of the AI teammate can become and, with that expansion, how much more supportive and intelligent it can be. This study will be a key first step in this expansion by exploring AI's role in transition phases and information sharing, which are among the most vital activities in teaming to advance coordination and subsequent performance. Consequently, the current research will contribute directly to the development of more human-centered collaborative AI systems, with the ultimate goal of advancing safer and more effective HATs that are applicable across contexts.

3 Methods

The current study employs a mixed-methods experimental design to capture and analyze variables relevant to team effectiveness and AI participation in complex team discussions across the teaming life cycle. The experiment used the well-known and validated synthetic task environment, the Cognitive Engineering Research on Team Tasks Uncrewed Aerial System-Synthetic Task Environment (CERTT UAS-STE). The between-subjects factors consisted of a 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) design. The within-subjects factors comprised six time points, divided into two transition phases (Transition Phase 1 and Transition Phase 2) and four Rounds (Round 1, Round 2, Round 3, and Round 4).

3.1 CERTT UAS-STE Task

The current study used the Cognitive Engineering Research on Team Tasks Uncrewed Aerial System-Synthetic Task Environment (CERTT UAS-STE) as the experimental platform for team collaboration. The CERTT STE models the operation of an uncrewed aerial system (UAS) and requires a team of three individuals to navigate, pilot, and photograph fictional target sites of interest. It is a proven platform for HAT research, having been reliably used for over a decade in human-human and human-autonomy-based teamwork research [17, 45, 46].

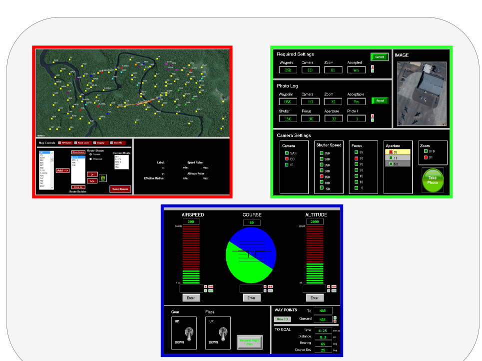


Fig. 1. Unique Console for Each Role within the CERTT STE. The DEMPC's Screen is Located in the Top Left (Red Border). The PLO's Screen is Located in the Top Right (Green Border). The AVO's Screen is Located on the Bottom (Blue Border).

Within the CERTT STE, each teammate has a unique role with specific features and actions they are responsible for completing. Specifically, the AVO (Pilot) operates the UAS heading, airspeed, altitude, and fuel restrictions by following a flight plan sent to them by the DEMPC (Navigator) (see bottom of Figure 1). The DEMPC develops and shares that flight plan for the UAS with the AVO, while also ensuring that the team is aware of any altitude, distance, and airspeed restrictions that may exist for each waypoint (see top left of Figure 1). Lastly, the PLO (Photographer) monitors sensors and communicates with AVO and DEMPC to ensure the correct camera settings are used for each target waypoint, which includes settings such as shutter speed, zoom level, camera type, and camera battery to ensure a good photo is taken before the UAS moves on to the next waypoint (see top right of Figure 1).

The overall goal of the team operating the UAS is to identify targets of interest within restricted zones (ROZs) by identifying and flying through an entry waypoint, entering an effective radius where a good photo can be taken, ensuring all UAS and camera restrictions are met to capture a good photo, photographing each target within the ROZ quickly and efficiently (2 to 3 targets per ROZ), and exiting the ROZ through the exit waypoint before moving on to the next ROZ. As such, the CERTT task is highly interdisciplinary, and each teammate must coordinate to accomplish their shared goal. The AI teammate completed the experiment as the DEMPC, while the participants took the AVO and PLO roles. The AI was chosen for the DEMPC role based on the success and ecological validity AI systems have in other navigational tasks [2, 33, 36].

3.2 Autonomous Teammate

In each condition, a confederate researcher assumed the role of the AI teammate's communication and behavior without the participant's knowledge. This design is consistent with the Wizard-of-Oz (WoZ) methodology, which enables the study to exert strong experimental control over the actions, communication, and design of the AI teammate, thereby improving internal validity [43]. This approach is similar to its use in previous HAT studies conducted within the CERTT STE platform [16, 46]. To successfully implement the AI using WoZ techniques, a detailed script for the AI teammate's communication and actions was developed through several full-length piloting sessions. The pre-defined communication script was also necessary to ensure consistency across teams.

The AI teammate was described to participants as having capabilities similar to those of ChatGPT and other popular large language models; however, participants were told that it had been trained only on information relevant to the CERTT task and to its specific SA-related information-sharing ability. This was done to simplify the script developed for the WoZ AI teammate. The script addressed two between-subjects factors. Specifically, it allowed the AI teammate to engage in one of three types of SA-related information-sharing and to participate in one of two transition phases throughout the experiment. Specifically, participants were informed that their AI teammate could not answer any questions unless they were directly related to their SA-related information-sharing ability or to the CERTT task itself. The AI teammate also responded to teammate requests with an affirmative or negative response, and it would respond affirmatively only if the request fell within the purview of the DEMPC role or was directly related to the SA information shared by the AI teammate. If the AI teammate were asked a question outside its purview or if the request would negatively impact team performance, it would respond that it could not complete that request. These restrictions also applied to the AI teammate's script throughout the transition phase.

3.2.1 Transition Phases. As a core focus of the current experiment, the sequential nature of the CERTT task rounds was utilized to understand the effect of AI participation in transition phases on HATs. These discussions were formally planned transition phases that occurred between rounds, enabling the teams to discuss improvements to team strategy, performance, information sharing, and goal alignment [40]. The first transition phase occurred between Rounds 1 and 2, and the second between Rounds 3 and 4. Using this design, the current study implemented two levels of the order-of-AI-transition-phase participation between-subjects factor. Specifically, the

AI either participated in the first transition phase between Rounds 1 and 2 (PN) or it participated in the second transition phase between Rounds 3 and 4 (NP). These levels were labeled as PN for "Participation-No Participation" and NP for "No Participation-Participation." The implementation of this transition phase involved providing participants with a brief description of its purpose (e.g., to discuss past performance and plan for future rounds), the duration of each phase, and the phase in which the AI teammate would participate with them. Because all team communication occurred via the CERTT text-chat system, the transition phases also used text-based chat in the Slack collaboration application. As such, the transition phase would begin once the researcher had guided all participants to their iPad tablets with the Slack application open, during which they would have text-based exchanges for six minutes.

3.2.2 Situation Awareness AI Information-Sharing Attribute. The additional information shared by the AI teammates beyond that typically required by the DEMPC role was scripted based on pilot studies and selected through discussions with the developers of the CERTT system. As such, the study implemented three AI SA-related information-sharing attributes: 1) Intra- and Extra-Team information-sharing (IET), which provided updates to the team regarding information changes that occurred inside and outside the team; 2) Augmenting Team Memory information-sharing (ATM), which sought to augment and enhance the team's ability to plan ahead and execute on long-term goals; and 3) Control information-sharing (Control), which did not share any extra information other than what was required to complete the taskwork and teamwork of the DEMPC role.

All AI teammates provided all the necessary information expected of the DEMPC navigator role, and any SA information sharing was in addition to this baseline DEMPC information. The control AI teammate represented only the baseline DEMPC information and did not share any additional information beyond what was required of the DEMPC role. However, the ATM AI teammate provided the number of targets upcoming in the next ROZ, any speed changes possible or required in the next ROZ (reminding them when those speed changes were required or available), and, if possible, a speed range that accommodated all the targets in the next ROZ. The IET AI teammate alerted the team whenever the UAS was not meeting airspeed requirements, warned them when altitude requirements were not met, communicated how to rectify the violation or warning, and notified them when dusk had fallen to help avoid poor photos.

3.2.3 Situation Awareness Roadblock. One feature the CERTT STE uses to stress teams and evaluate their ability to use effective team SA for coordination is a roadblock, which, in this case, was represented by a system failure occurring once per round. These system failures were implemented as a temporary loss of specific data readouts for AVO and PLO (never simultaneously), which always occurred once in the second ROZ of a round. The system failure affected the PLO role in the first two rounds, lasting 4.5 minutes, while the last two rounds affected the AVO role for 1.5 minutes. This time difference was due to pilot testing, which revealed that AVO system failures typically added 2-3 minutes to recovery from course deviations. To mitigate the negative impact of these failures on their shared performance, teammates had to actively communicate which of them was experiencing the failure, so that the other two teammates could relay the specific information needed to overcome the system failure. Specifically, the AVO failure required the team to recognize that the PLO teammate had the bearing information they would share with AVO, which would be used to correct their course. If the PLO experienced a failure, the team had to recognize that they would need the distance to the target reported to them as they approached, to prepare to take a photo, and know when to take it. All this information was available to the team regardless of whether they were in the ATM, in the IET, or under control SA-related information-sharing conditions. However, the three AI SA information-sharing attributes handled the failures differently. The ATM and IET AI teammates both alerted the team to the system failure. Subsequently, they provided additional information in line with their SA-related information-sharing attributes. Specifically, the IET AI teammate alerted the team to a failure and its affected components. Then, they notified the team that they would automatically share the information needed for the individual to continue operating effectively (bearing or distance to the target). The ATM AI teammate also alerted the team to a failure, identified its affected components, and informed the team of the occluded information and what information the teammate needed to continue operating effectively. Lastly, the control AI teammate neither alerted the team to the failure nor provided any additional information.

3.3 Participants

The study recruited 74 participants from a large southeastern university, yielding 37 teams, each with two participants. However, five teams were dropped due to technical glitches, and one team was excluded because it failed the manipulation check. As such, the final dataset comprised of 62 participants (45 participants identified as women, the remainder as men; $M_{age} = 20.4, SD_{age} = 3.13$), which made up 31 teams where each between-subjects condition had at least ten teams (the control condition had 11 teams as one other control condition team's survey data was corrupted). This sample size aligns with previous teaming research that has utilized the CERTT platform [17, 45, 46], which calls for at least ten teams per between-subjects condition. Each session lasted approximately three hours, and participants were compensated for their time with either course credit or $30 gift cards, depending on their recruitment method. This research was conducted in accordance with all relevant laws and institutional guidelines and was approved by the institution's review board. Participants provided informed consent before their participation.

3.4 Procedure

Upon arrival, participants were randomly assigned to a team role and to the between-subjects conditions. Informed consent was obtained, and then the experimenter explained the study's purpose to the participants in detail. Participants completed an interactive PowerPoint training session on the CERTT task and their specific role, during which they could ask questions. Afterward, participants underwent a 15-minute hands-on training session to practice using the simulation environment's controls and to work with one another, including the AI teammate. Once training was complete, the experimenter took questions from participants. At this point, participants began the first round, which lasted 20 minutes; all subsequent rounds followed the same 20-minute duration. After the first round, participants completed the first of six surveys on an iPad, as the study employed a repeated-measures design (see Figure 2). Once the first survey was completed, the participants were briefed on the goals of the transition phase and reminded whether the AI teammate would be joining them during the upcoming transition phase. The experimenter then switched their iPad tablets to the Slack application and conversed with one another via text chat for six minutes during the transition phase. Once the transition phase had ended, the participants were directed back to their desktop computers to complete the second round, followed by another survey. Participants were given a five-minute break after Round 2, due to the length of the session. After the break, the participants completed the next two rounds in the same style as the first two, with a six-minute transition phase occurring between Rounds 3 and 4. After completing all rounds and surveys, participants were invited to a semi-structured focus group interview lasting 10 minutes. Once the interview was completed, the participants were given a verbal manipulation check, in addition to their survey-based manipulation check, and debriefed about the WoZ deception. They were then given their incentive and dismissed.

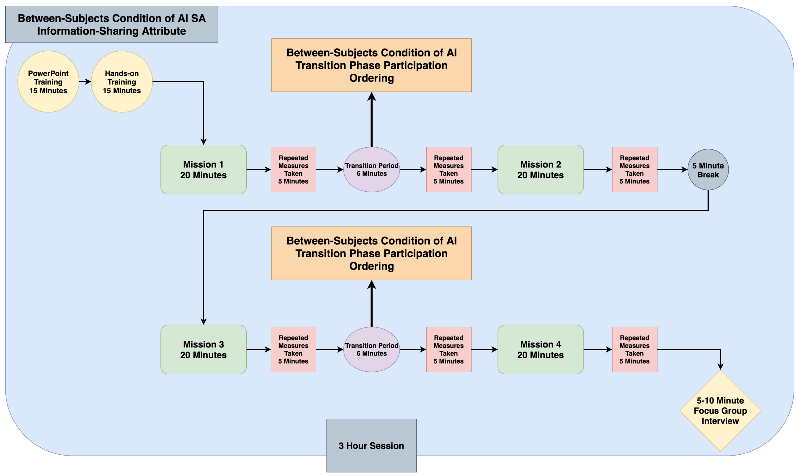


Fig. 2. Study Timeline Showing All Repeated Measures.

3.5 Quantitative Measures

3.5.1 Team Target Processing Efficiency (Team Performance). Participants' team performance was measured as an outcome-based measure of team effectiveness. Specifically, team performance was measured using target processing efficiency. Target processing efficiency utilizes the time teams spend within a target's effective radius to obtain a clear photo. Thus, a higher score indicates greater team efficiency. Each team begins a round with 1,000 points for each target, and points are deducted from that total based on the number of seconds inside the effective radius of the target, and there is a 200-point penalty for not taking a good photo [12]. Scores for each target were averaged within each round, yielding an average target-processing efficiency score for that round, with higher values indicating greater objective team performance.

3.5.2 Perceived Team Effectiveness. Participants' perceived team effectiveness was measured at each repeated measures time point using the team effectiveness scale developed by Rentsch and colleagues [57]. This scale comprises eight items, each rated on a seven-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree." Responses to the eight items were averaged per participant, with higher values indicating greater perceived team effectiveness.

3.5.3 Perceived Shared Mental Model with Human Teammate. Participants' perception of an SMM with their human teammate was measured using a shortened version of the scale developed by van Rensburg and colleagues [72]. This adaptation of the survey consisted of 10 items, each rated on a seven-point Likert scale ranging from "Strongly Disagree" to "Strongly Agree." The 10 items were drawn from the execution, interaction, and temporal sub-scales of the five-factor mental model scale. These factors were chosen over equipment and composition because they were less relevant to the current task, and team and task mental models are the primary focus of team cognition research [42]. Each participant responded to 10 items at each repeated-measures time point. Responses to each of the ten items were averaged per participant, with higher values indicating a greater perception of an SMM with their human teammate.

3.5.4 Trust in the Human and AI Teammates. Participants' trust in their two teammates was measured using an instrument based on the outcomes of trust identified by [37] and utilized in previous HAT trust research [63, 64]. This scale consisted of six items, each rated on a seven-point

Likert scale, ranging from "Strongly Disagree" to "Strongly Agree." Participants answered the six items for each teammate, totaling 12 items, and responded to them at each repeated-measures point shown in the timeline (Figure 2). Responses to each set of six items were averaged per participant, with higher values indicating greater trust in the relevant teammate.

3.6 Qualitative Data & Analysis

3.6.1 Focus Group Interview. The current study conducted focus group interviews with teams after they completed the final round and the survey. One trained experimenter led the focus group interview following a semi-structured interview protocol. The interview lasted between five and ten minutes, with questions focusing on their experience going through the transition phases with and without the AI teammate, how the participants perceived the AI teammate's contributions to team cognition, how the AI information-sharing influenced transition phase discussions, and how their ability to cooperate effectively developed throughout the experience. Thus, the focus group interview enabled the study to provide more comprehensive answers to the research questions by eliciting participants' lived experiences.

3.6.2 Qualitative Analysis. The focus group interview data were transcribed using Otter.AI and then analyzed using thematic analysis [5, 27, 28, 68]. Specifically, the data was analyzed in four phases: 1) each transcript was reviewed to gain an understanding of how the participants reacted to the presence of the AI, or lack thereof, in transition phases and how the AI teammate's SA information-sharing attribute influenced their SA development; 2) the transcripts were re-reviewed to identify major themes and sub-themes describing the impact of the AI teammates' participation in the transition phases early versus later in their life cycle along with the AI teammate's influence on their SA development; 3) the themes and sub-themes were reviewed and discussed with the other authors of the study until agreement was achieved; 4) individual quotes were selected to represent the themes and sub-themes; and 5) themes and sub-themes were reviewed one final time with the authors using the quotes selected in Step 4 to ensure the results were a representative distillation of the participants' experiences on the impact of AI participation in the transition phases early versus late in their life cycle and how the AI SA-related information-sharing altered those discussions for better or worse.

4 Results

To answer the RQs posed by the current study, the results have been organized into two overarching sections. The first section presents the quantitative analysis, including team trust, perceived team effectiveness, perceived SMM, and team performance. The second section details the qualitative analysis, which provides additional context to the quantitative findings by highlighting qualitative themes. The section reporting the quantitative analysis is organized by dependent variable, and the qualitative results section is organized by the major themes identified in the analysis.

4.1 Quantitative Results

The quantitative results presented in this section are organized by dependent variable and divided into two categories: whether the analysis examines the dependent variable across the four rounds or across the two transition phases. First, analyses of participants' trust and team cognition are presented, followed by analyses of measures of perceived team effectiveness and objective team performance. Unless otherwise stated, all statistical assumptions for tests (i.e., normality, homoscedasticity) were met for analyses. Every analysis used Holm-corrected post hoc tests and reported marginal means. When violations of sphericity were detected, Greenhouse-Geisser's corrected degrees of freedom were used. All tests were evaluated for assumptions of normality (Q-Q

Plots) and homoscedasticity (Levene's test), for which all tests were nominal except for a violation in the test on trust during the two transition phases ($F(5, 54) = 6.19$, $p < .001$). However, given that ANOVA is generally robust to such violations in balanced designs [65], no transformations were made. All analyses examined main and interaction effects, directly answering RQs 1, 2, and 3.

4.1.1 *Trust in the AI Teammate.*

The trust in the AI teammate data for the missions comprised 80 entries across all between-subjects conditions and 120 entries across all within-subjects conditions. The trust in the AI teammate data for the transition phases comprised 40 entries in the between-subjects condition and 60 in the within-subjects condition. One control condition team was excluded from the survey data due to a technical issue with the survey platform.

Trust in the AI Teammate Across Rounds. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 4 (Round: R1, R2, R3, R4) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' trust in their human teammate across the four rounds (within-subjects). The analysis revealed a significant main effect of round on participants' trust in the AI teammate ($F(3, 162) = 4.23$, $p = .007$, $\eta_p^2 = .07$; see Figure 3). Post-hoc tests showed that participants' trust in the AI teammate was significantly higher after Round 1 ($M = 3.99$, $SE = .06$) than after Round 3 ($M = 3.69$, $SE = .08$).

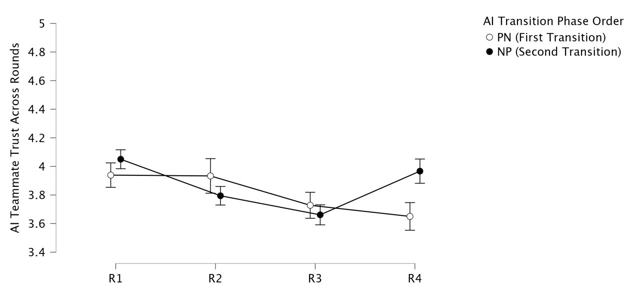


Fig. 3. Trust in the AI Teammate by Round and AI Transition Phase Ordering. Error Bars Represent Normalized Standard Error.

This main effect was qualified by a significant disordinal interaction effect between round and AI transition phase ordering ($F(3, 162) = 2.81$, $p = .041$, $\eta_p^2 = .05$; see Figure 3). Deconstructing the interaction effect with simple main effects analyses using round as the simple effect factor found a significant simple main effect of NP ($F(3, 162) = 6.00$, $p < .001$, $\eta_p^2 = .07$). Specifically, participants working with the AI that participated in the second transition phase only had higher trust in the AI teammate after Round 1 ($M = 4.05$, $SE = .09$) than after Round 2 ($M = 3.79$, $SE = .10$) and after Round 3 ($M = 3.66$, $SE = .10$). However, participants trust was higher after Round 4 ($M = 3.97$, $SE = .11$) than after Round 3.

Trust in the AI Teammate Across Transition Phases. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 2 (Transition Phase: TP1, TP2) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' trust in their AI teammate across the two transition phases (within-subjects). The analysis revealed all effects to be non-significant; see Figure 4.

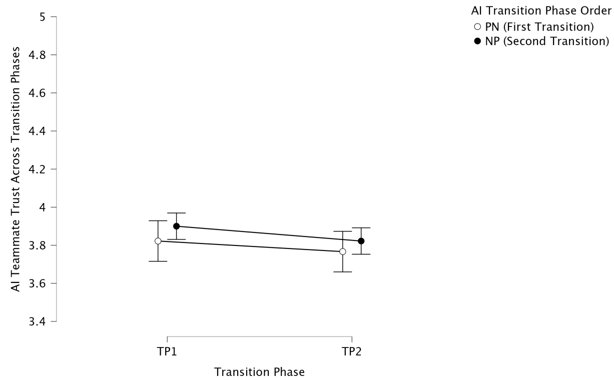


Fig. 4. Trust in the AI Teammate by AI Transition Phase Order Across the Two Transition Phases. Error Bars Represent Normalized Standard Error.

4.1.2 Trust in the Human Teammate. The trust in the human-teammate data for the missions comprised 80 entries across all between-subjects conditions and 120 entries across all within-subjects conditions. The trust in the human teammate data for the transition phases comprised 40 entries in the between-subjects condition and 60 in the within-subjects condition. One control condition team was excluded from the survey data due to a technical issue with the survey platform.

Trust in the Human Teammate Across Rounds. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 4 (Round: R1, R2, R3, R4) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' trust in their human teammate across rounds (within-subjects). The analysis revealed all effects to be non-significant; see Figure 5.

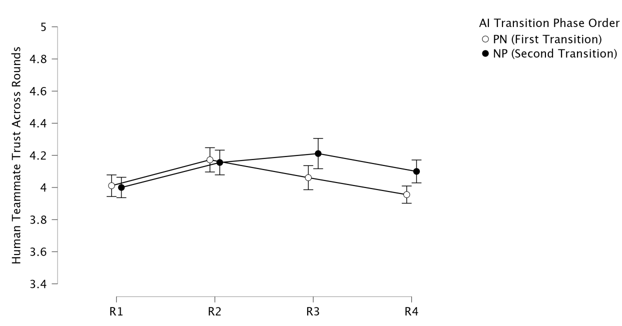


Fig. 5. Trust in the Human Teammate by Round and AI Transition Phase Ordering. Error Bars Represent Normalized Standard Error.

Trust in the Human Teammate Across Transition Phases. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 2 (Transition Phase: TP1, TP2) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' trust in their human teammate across the two transition phases (within-subjects). The analysis revealed all effects to be non-significant; see Figure 6. Though there was a marginally significant ($p < .10$) main effect of transition phase ($F(1, 54) = 3.51$, $p = .066$, $\eta_p^2 = .06$; see Figure 6).

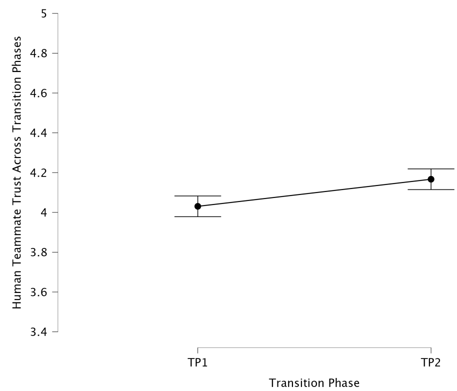


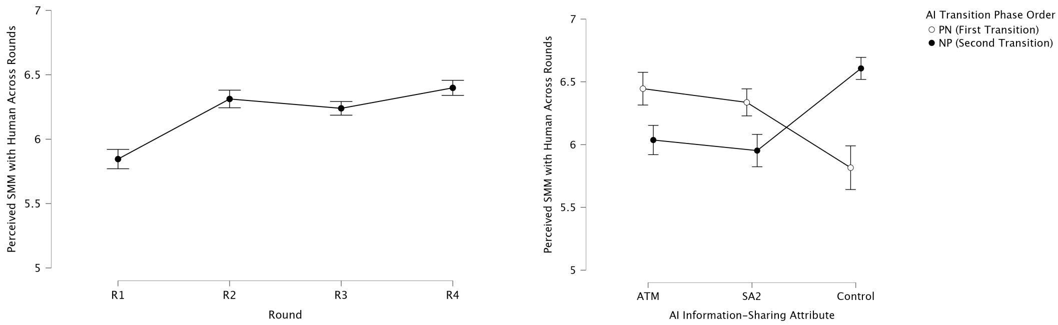
Fig. 6. Trust in the Human Teammate by AI Transition Phase Order Across the Two Transition Phases. Error Bars Represent Normalized Standard Error.

4.1.3 Perceived Shared Mental Model with Human Teammate. The perceived SMM with the human teammate data for the missions consisted of 80 entries for all between-subjects conditions and 120 entries for all within-subjects conditions. The perceived SMM with the human teammate data for the transition phases included 40 entries for the between-subjects condition and 60 for the within-subjects condition. One control condition team was excluded from the survey data due to a technical issue with the survey platform.

Shared Mental Model with Human Teammate Across Rounds. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 4 (Round: R1, R2, R3, R4) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' SMM with their human teammate across rounds (within-subjects). There was a significant effect of round on participants' SMM with their human teammate ($F(2.52, 136.19) = 14.17$, $p < .001$, $\eta_p^2 = .21$; see Figure 7a). Post-hoc tests showed that participants perceived SMM with their human teammate was significantly lower after Round 1 ($M = 5.85$, $SE = .12$) than after Round 2 ($M = 6.31$, $SE = .09$), Round 3 ($M = 6.24$, $SE = .10$), and Round 4 ($M = 6.40$, $SE = .10$). Participants perceived SMM with their human teammates was also significantly lower following Round 3 than following Round 4.

The analysis also revealed a significant disordinal interaction effect between AI information-sharing attribute and AI transition phase ordering on participants perceived SMM with their human teammate ($F(2, 54) = 5.27$, $p = .008$, $\eta_p^2 = .16$; see Figure 7b). Follow-up simple main effects analysis using order of AI transition phase participation as the simple effect factor deconstructed this result, finding a significant simple main effect for the Control AI information-sharing attribute condition ($F(1, 54) = 6.94$, $p = .017$, $\eta_p^2 = .12$). Specifically, for participants working with the control AI information-sharing attribute in the PN condition had worse perceived SMM with their human teammate ($M = 5.82$, $SE = .21$) than those in the NP condition ($M = 6.61$, $SE = .21$).

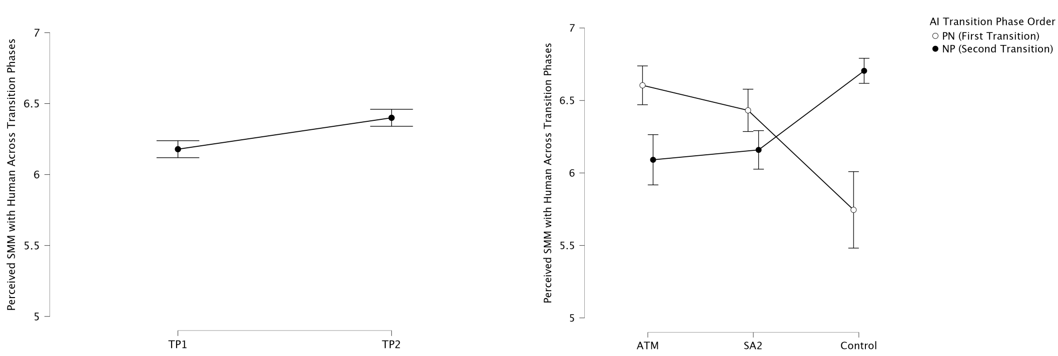
Shared Mental Model with the Human Teammate Across Transition Phases. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 2 (Transition Phase: TP1, TP2) mixed RMANOVA was conducted to assess the effect of AI



(a) Within-Subjects main effect. (b) Between-Subjects interaction effect.

Fig. 7. Perceived Shared Mental Model with the Human Teammate by Round (Figure 7a) and the Interaction Between the AI Information-Sharing Attribute and AI Transition Phase Ordering (Figure 7b). Error Bars Represent Normalized Standard Error.

information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' perceived SMM with their human teammate across the two transition phases (within-subjects). The analysis revealed a significant main effect of transition phase on participants' perception of a SMM with their human teammate ($F(1, 25) = 5.13$, $p = .032$, $\eta_p^2 = .17$; see Figure 8a). Specifically, participants perceived a weaker SMM with their human teammate after the first transition phase ($M = 6.18$, $SE = .09$) than the second transition phase ($M = 6.40$, $SE = .10$).



(a) Within-Subjects main effect. (b) Between-Subjects interaction effect.

Fig. 8. Perceived Shared Mental Model with the Human Teammate by Transition Phase (Figure 7a) and the Interaction Between the AI Information-Sharing Attribute and AI Transition Phase Ordering (Figure 7b). Error Bars Represent Normalized Standard Error.

The analysis also revealed a significant disordinal interaction effect between AI information-sharing attribute and AI transition phase ordering on participants perceived SMM with their human teammate across the two transition phases ($F(2, 54) = 7.00$, $p = .002$, $\eta_p^2 = .21$; see Figure 8b). The interaction effect was deconstructed using simple main effects analysis with order of AI transition phase participation as the simple effect factor, which revealed a significant simple main effect for the Control AI information-sharing attribute condition ($F(1, 54) = 6.91$, $p = .017$, $\eta_p^2 = .16$). Specifically, the perception of a SMM between human teammates for teams with the AI participating in the first transition phase (M = 5.74, SE = .26) were significantly worse than those with the AI participating in the second (M = 6.71, SE = .26).

The analysis also indicated a significant three-way interaction effect ($F(2, 54) = 3.40$, $p = .041$, $\eta_p^2 = .11$); however, deconstructing the interaction effect by running RMANOVAs on relevant subsets of the data did not reveal any significant two-way interaction effects. Accordingly, the three-way interaction effect could not be decomposed.

4.1.4 Perceived Team Effectiveness. The perceived team effectiveness data for the missions comprised 80 entries across all between-subjects conditions and 120 entries across all within-subjects conditions. The perceived team effectiveness data for the transition phases comprised 40 entries in the between-subjects condition and 60 in the within-subjects condition. One control condition team was excluded from the survey data due to a technical issue with the survey platform.

Perceived Team Effectiveness Across Rounds. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 4 (Round: R1, R2, R3, R4) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' perceived team performance across rounds (within-subjects). There was a significant main effect of round on perceived team effectiveness ($F(2.66, 143.49) = 18.64$, $p < .001$, $\eta_p^2 = .26$; see Figure 9). Post-hoc test showed that participants perceived team effectiveness after Round 1 (M = 5.50, SE = .10) was significantly lower than after Round 2 (M = 5.91, SE = .11), Round 3 (M = 5.92, SE = .12), and Round 4 (M = 6.21, SE = .11). Lastly, perceived team performance after Rounds 2 and 3 were also significantly lower than after Round 4.

This main effect was qualified by a significant disordinal interaction effect between round and AI transition phase ordering ($F(2.66, 143.49) = 2.82$, $p = .048$, $\eta_p^2 = .05$; see Figure 9). Deconstructing the interaction effect with simple main effects using round as the simple effect factor, there was a significant main effect for PN ($F(3, 162) = 15.31$, $p < .001$, $\eta_p^2 = .21$) and NP ($F(3, 162) = 6.58$, $p < .001$, $\eta_p^2 = .11$). Holm corrected post hoc tests of the PN simple main effect revealed that participants perceived performance after Round 1 (M = 5.43, SE = .15) was significantly lower than Round 2 (M = 6.10, SE = .13), Round 3 (M = 6.03, SE = .20), and Round 4 (M = 6.25, SE = .16). Examining the NP simple main effect showed that participants perceived performance after Round 4 (M = 6.17, SE = .14) was significantly better than after Round 1 (M = 5.58, SE = .14), Round 2 (M = 5.72, SE = .17), and Round 3 (M = 5.80, SE = .14).

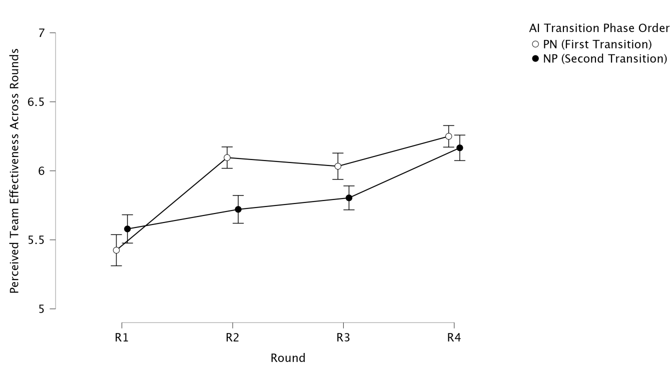


Fig. 9. Perceived Team Effectiveness by Round and AI Transition Phase Order. Error Bars Represent Normalized Standard Error.

Perceived Team Effectiveness Across Transition Phases. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 2 (Transition Phase: TP1, TP2) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on participants' perceived team effectiveness across the two transition phases (within-subjects). There was a significant main effect of transition phase on perceived team effectiveness ($F(1, 54) = 19.94$, $p < .001$, $\eta_p^2 = .27$; see Figure 10). Specifically, participants' perceived team effectiveness following the second transition phase ($M = 6.09$, $SE = .10$) was significantly greater than after the first transition phase ($M = 5.69$, $SE = .09$). All other effects were non-significant.

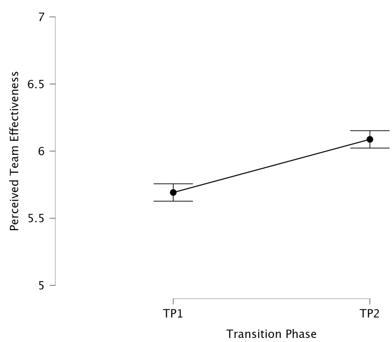


Fig. 10. Perceived Team Effectiveness by Round and AI Transition Phase Order Across the Two Transition Phases. Error Bars Represent Normalized Standard Error.

4.1.5 Objective Team Performance (Average Target Processing Efficiency). The team performance data included 40 entries for the ATM and IET conditions, and 44 entries for the control condition. The AI transition phase participation ordering manipulation saw 60 entries for the PN condition and 64 for the NP condition.

Team Target Processing Efficiency. A 2 (Order of AI Transition Phase Participation: PN, NP) x 3 (AI Information-Sharing Attribute: ATM, IET, Control) x 4 (Round: R1, R2, R3, R4) mixed RMANOVA was conducted to assess the effect of AI information-sharing attribute and transition phase participation ordering (both between-subjects) on teams' target processing efficiency across rounds (within-subjects).

The analysis showed that AI transition phase order had a significant main effect on teams' target processing efficiency ($F(1, 25) = 5.13$, $p = .032$, $\eta_p^2 = .17$; see Figure 11). Specifically, teams that had the AI teammate participate in the first transition period ($M = 883.27$, $SE = 13.69$) had significantly worse target processing efficiency than teams whose AI teammate participated in the second transition period ($M = 927.16$, $SE = 13.69$).

4.2 Qualitative Results

The focus group interview data provided additional context to the quantitative results, allowing participants to offer direct commentary on the lived experiences that shaped their survey responses and team behaviors throughout the four rounds. As such, this qualitative data is imperative to adequately answering the RQs posed by the current study. Specifically, the qualitative data provides two themes that help contextualize the quantitative findings. The first theme addresses RQs 1 and 2, examining the role of AI participation in discussions during the transition phase. The second

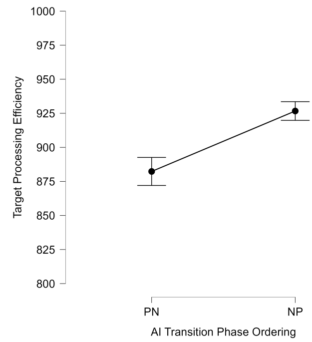


Fig. 11. Team Target Processing Efficiency by AI Transition Phase Order. Error Bars Represent Standard Error.

theme addresses RQs 2 and 3 by examining how the three levels of AI SA information-sharing contributed to the development of team cognition over time. These themes further contextualize the quantitative results initially provided to address the RQs.

4.2.1 The Benefits of AI Participation in Transition Phases are More Substantial Later in A Team's Life Cycle. Starting with qualitative themes related to RQ1 and RQ2, we explore the impact of AI participation during transition phases and the timing of that participation within the team's overall life cycle. The quantitative results indicate that participation in these phases significantly influenced target processing efficiency and perceived team performance. While the observed benefits of AI participation during later transition phases were not substantial, teams that engaged with AI during these periods exhibited objectively higher target-processing efficiency. This outcome may be linked to the nature of the discussions taking place during the two transition phases:

> *"During the first transition period, I'm still getting the hang of things and I didn't fully understand the task yet. So I don't know necessarily what to ask, but then the second transition period, I feel like it went really well. We got through what we needed and talked about how to fix the system crashes and how to help each other." (Team 6-ATM-PN)*

Participants conveyed that the first transition phase was frequently used to understand fundamental aspects of the task, as they were *"still getting the hang of things and didn't fully understand the task."* Because of this novelty, teams didn't *"know necessarily what to ask."* Still, by the time of the second transition phase, the topics of conversation were significantly more complex and focused on *"how to fix the system crashes and how to help each other."* As such, the participants reported that the second transition period was frequently associated with higher-level coordination and a direct focus on improving resiliency through team SA and SMMs compared to the first.

Because of the nature of the discussions during the second transition phase, the participation of the AI teammate in the second transition allowed the team to ask questions related directly to improving coordination and performance:

> *"The second one because we got to a point where we were more proficient at the task, and because of that, it meant we actually knew what questions to ask. Our questions could be more specific, they could be more tailored to achieving a higher score as opposed to just how do we use this to begin with." (Team 35-Control-NP)*
> *"I would prefer it in the second one. There were a few things that I actually would have wanted to ask, which in the first one, I felt like I hadn't even gotten to that point where I knew what questions to ask." (Team 22-IET-PN)*

Participants viewed the second transition period as an opportunity to refine their team's abilities and team cognition, once they had gained a solid understanding of the task's basics. Specifically, teams *"knew what questions to ask. We could be more tailored to achieving a higher score."* This sentiment was present across all levels of the two manipulations, as Team 22 stated they would have *"prefer[ed] it [the AI teammate] in the second [transition phase]"* for the same reason the teams with the AI participating in the second transition phase stated they appreciated having it participate when it did.

However, having the AI teammate participate in the first transition phase also held its own unique benefits in establishing an accurate shared understanding:

> *"Yeah, I feel like they were the expert in their role and helped us work together at the beginning." (Team 20-IET-PN)*
> *"I think they [the transition phases] were good, especially the first one because I was a little bit worried about making mistakes...but having that reassurance that we were both at that same position of getting used to things gave me more confidence going into the later rounds." (Team 22-IET-PN)*

Although not measured in the current study, these teams may be reporting their appreciation for the opportunity to establish more accurate SMMs for the task early on. Asking the AI teammate questions related to establishing a precise understanding of the task was especially helpful because *"they were the expert in their role,"* which allowed the teams to leverage that information and improve their ability to *"work together at the beginning"* of the task. Having the AI teammate in the first transition phase also gave *"reassurance that we [the two human teammates] were both at that same position of getting used to things."* Having that reassurance from the first transition phase then had a knock-on effect that gave them *"more confidence going into the later rounds."* This higher confidence is actually reflected in the quantitative results as both the PN and NP teams experienced boosts to perceived team effectiveness following a transition phase where the AI teammate participated.

4.2.2 Gradually Sharing More Information with Teammates Can Improve Information Acceptance. A central question of the current study, which ties RQ1 and RQ2 together, is the timing of AI information-sharing and participation during the transition phase. One crucial issue in team development is the development of experience with the AI teammate, which makes human teammates more likely to engage with and accept the AI teammate's information. The current study reveals themes to this question of timing and acceptance, as it demonstrates that utility alone is not the only piece of the puzzle and that the way the AI teammate conveys its utility over time is similarly critical:

> *"When I was putting the bearings in for the next target, I knew that I had to decrease the speed because it reminded me. So that helped a lot because I would not have remembered it." (Team 11-ATM-PN)*
> *"[Improved SA] definitely at the beginning. I think it did by sending the little reminders, especially when the system failed." (Team 23-IET-PN)*

A common theme among teams was that trust and acceptance in the AI teammate were established early on through reminders, which can be designed to convey the utility of an AI teammate unobtrusively and effectively. Team 11 stated that the AI teammate contributed to their SA when the AI teammate *"reminded me [to decrease the speed]. That helped a lot because I would not have remembered it."* The same sentiment was true for Team 23, which was in a different AI SA attribute altogether but conveyed its utility during a challenging time by *"sending little reminders, especially when the system failed."* This statement also emphasizes the need to have the AI teammate step up in some way when the team faces significant roadblocks.

AI teammates also convey their utility by answering questions that their human teammates have for them while they are learning the taskwork and teamwork required to accomplish the team's shared goals:

> *"I felt less embarrassed to ask questions to the AI because it's a computer." (Team 6-ATM-PN)*
> *"When I was telling my teammate stuff I felt so annoying, but with the AI I just didn't have to worry about that because I want to be nice, but the AI doesn't care." (Team 11-ATM-PN)*
> *"...It's like you said, you can't be judged because it's a computer; you'll ask more questions." (Team 6-ATM-PN)*

The inherent advantages of working with AI systems extend beyond technical benefits to include social advantages. As all of Team 6 states *"I felt less embarrassed to ask questions to the AI because it's a computer"* distinctly because *"you can't be judged because it's a computer."* This sentiment is mostly accurate, though in some cases, poor training methods and data can lead to biased AI [58]. Because of this advantage, some teams in the current study felt comfortable *"ask[ing] more questions"* than they typically would have. As such, their performance and team cognition would be improved, given the AI teammate's accurate information about the task.

Despite these advantages offered by the AI teammate from a technical and social standpoint, the AI teammate and their contributions to the team were not immediately accepted without scrutiny:

> *"I felt like I would trust a human more than an AI, but after working with it my trust in it was the same." (Team 21-IET-NP)*

There was a sentiment from teams that their initial trust in the AI teammate was at a disadvantage. As Team 21 stated *"I felt like I would trust a human more than an AI,"* and the quantitative data also showcased a similar sentiment as trust fell slightly at the beginning of the teams' life cycle and reduced on average over time; however, the quantitative data showed that only the NP teams trust in the AI teammate recovered to initial levels after Round 4 after they had the opportunity to speak with the AI teammate in the second transition phase. Still, the qualitative data supports the trend that *"after working with it [the AI teammate], my trust in it was the same [as their trust in the human teammate]."* This sentiment shows that the acceptance of contributions by the AI teammate can overcome initial inequity through effective design and meaningful discussions held in the transition phases, reviewing action phase activities.

5 Discussion

The current study represents one of the first empirical examinations of AI participation in transition phases over time, of how it enables SA-related information sharing among the same AI teammates, and of how these factors affect critical team constructs within HATs. Specifically, the current study addressed RQ1, which examined how AI participation in transition phases affects HATs' trust, perception of a SMM with human teammates, and team performance. The study also addressed RQ2, which examined whether the effect of AI participation in transition phases differed when that participation occurred early versus late in the team's life cycle. Lastly, the study addressed RQ3 by examining whether different AI SA information-sharing attributes affected team interaction throughout the teaming life cycle.

5.1 AI Teammate Participation in Transition Phases Has Significant Impacts on Team Outcomes

The temporal dynamics of teams are a critical factor in effective teaming, and the participation of AI teammates clearly influences this aspect, as indicated by the results of the current study. Unfortunately, the impact of AI participation in team transition phases on team processes and outcomes has only recently begun to be examined [54]. Despite this shortcoming, the current study has revealed fascinating insights into how AI can enhance the abilities and outcomes of HATs. For example, in addressing RQ1.3, the study found that teams that interacted with their AI teammate during the second transition-phase discussion outperformed those that did not. This result could be a consequence of how teams develop over time, as the qualitative results alluded to, with teams in the second transition phase with AI being able to engage in more impactful discussions that influenced their performance. Participants' perceived team effectiveness also increased significantly following a transition phase, but *only* when the AI teammate participated in that phase. Traditional teaming literature echoes these results, as teams engage in more complex task-related discussions over time within their team [29, 40]. Still, the AI teammate used in the current study engaged in relatively simple forms of information-sharing, not including predictive analytics, adaptive support, or collaborative creative problem-solving. While the current experiment serves as a strong and necessary starting point for internal validity, it is critical to acknowledge that the full potential and interactivity of AI teammates are even more sophisticated.

These transition phases represent a clear opportunity to improve the ability and reception of AI teammates by developing them to operate using human-centered techniques throughout the natural cycle of teams. If they cannot support these phases, they will be unable to achieve the higher levels of teaming efficiency, safety, and performance that such teams promise in the near future [47, 61, 66]. The qualitative results also support this point, as many participants reported accepting the AI teammate more when it could answer their numerous questions over time. If the AI teammate were available only during action phases and could not participate in transition-phase discussions, there would be significantly fewer opportunities to ask those questions and to accept it as a teammate. Asking questions throughout the action phase can also reduce task performance due to distraction and cognitive overload [6]. From these findings, there is strong evidence that AI teammates' participation in team transition-phase discussions can substantially affect team outcomes. Such results encourage the notion that designing, developing, and implementing AI teammates that operate at the same level as human teammates is essential. Lastly, the full participation of AI teammates in the development of team cognition will require prediction of future states (e.g., Level 3 SA [22]), adaptation to varying contexts (e.g., [77]), and support of new team and individual capabilities (e.g., [76]).

5.2 AI Participation in Transition Phases Altered Team Perceptions

The current experiment also examines the nuanced effects of AI transition-phase participation on team cognition-related variables, such as trust and perceived SMMs among human teammates. The study's results showed no significant impact on participants' trust in their human teammate; however, on average, participants' trust in the AI teammate declined over time. These results, addressing RQ1.1, reveal an inconsistency in trust in the AI teammate despite its perfect reliability throughout the experiment. However, regarding the importance of AI participation in transition phases, the significant interaction effect indicated that participants' trust in their AI teammate recovered after Round 4 for teams with the AI teammate participating in the second transition phase (NP). This result highlights a direct connection between transition phases and trust in the AI teammate, a crucial indicator of HAT performance [45]. Such perceptual findings align with previous studies, which highlight that the mere perception of working with an AI teammate can significantly impact objective behavior, information sharing, and perceptions [18, 51, 63]. These effects likely extend to interactions and perceptions during transition phases, so there may be instances in which human teammates do not want their AI teammate to participate in a transition phase, with privacy being one such example [39]. In fact, the significant interaction effect, highlighting that the control AI teammate harmed participants' perceived SMM with their human teammate, could be attributed to it inducing greater cognitive load on the team during the transition-phase discussion. Cognitive Load Theory states that under greater cognitive processing demands, the acquisition of schema-based knowledge, such as SMMs, is significantly hindered [69]. This adverse effect was pronounced in teams with an AI teammate participating in the first transition phase, given that Tuckman's stages of team development detail the "Forming," "Storming," and "Norming" stages at the beginning of team development, where schema development occurs [71].

The qualitative themes of the current study highlight not only the impact of AI participation in transition phases on team perceptions but also the interaction between AI SA information-sharing attributes and these perceptions. In one qualitative theme, all three AI teammate types were described as helpful throughout the transition phase they participated in, regardless of whether it was the first or second, with the first and second types being useful for different reasons, as discussed in the previous section. Examined alongside the only significant quantitative interaction between the two manipulations, it is likely that the exact information shared does not matter, especially since the interaction only affected the control AI teammate. Instead, it is more important that the team and the AI have the opportunity to discuss the information. Such a finding aligns well with previous research on AI explainability and with the efficacy of AI information-sharing more generally [22, 48, 60, 76]. However, participants' acceptance of the AI and its information was influenced by the manner in which it was delivered over time. While not accompanied by quantitative results, the qualitative results indicated that many participants saw their AI teammate as a cautious resource, something to learn about, trust, and then learn from over time, which is akin to the reliability and social aspects of the recent models on human-autonomy and human-automation trust [9, 35]. This is important to note, as AI teammates will be critical fixtures within teams tasked with improving team abilities and outcomes beyond what either entity, human or AI, can achieve alone [47, 54, 66]. As such, this finding on perceived performance is indicative of stronger team cohesion as the team develops collectively, rather than within silos [24, 55], which some HATs have been known to experience [51]. These results describe the nuanced effects of AI teammate participation in team transition phases on HATs, along with the theorized pitfalls, advantages, and opportunities for growth in research, design, and development for collaborative AI.

5.3 Design Recommendations

Grounded in the current study's findings, two design recommendations are provided for CSCW, HF, and HCI researchers and practitioners to help improve HATs. These recommendations primarily focus on the participation of AI teammates during transition phases, including when to engage and how to maximize their effectiveness in information sharing and exchange. These findings align with recent research on AI teammate support for team cognition and information-sharing [22, 60], which are critical areas of improvement for HATs that must be addressed over the coming decade.

5.3.1 AI Teammates Should Participate in Transition Phases. The most critical design recommendation supported by the current study is the need to design and develop AI teammates that are capable of engaging in transition-phase discussions. These discussions are vital to team development [40] and are a necessary design feature if AI teammates are to be perceived as engaging in the full spectrum of teamwork behaviors [38]. To accomplish this, practitioners should recognize when transition phases will occur for the task their AI teammate will be asked to engage in, what information it should be aware of to be productive in the discussion, and what goals the team may have going into the discussion. Recognizing that not all transition phases will be as well-defined as those in the current study (e.g., knowledge workers), it is critical to design AI teammates more effectively. For example, in knowledge work teams, an AI teammate may be designed to recognize when meeting topics are geared toward planning and strategy, allowing it to understand when to engage in transition-phase processes. AI teammates could also prompt workers to consider such issues if the AI model is trained to recognize and highlight shortcomings in the team's current approach. These goals will likely be dictated by past team performance, as poor outcomes will prompt discussion of adapting strategy, goal alignment, or other behaviors more directly associated with team performance. Furthermore, AI teammates should be prepared to engage in explainability behaviors whenever transition phases occur, as they not only serve as a natural medium for these discussions [52] but can also be explicitly tailored to the context of previous performance, aligning easily with the focused topics of transition phases. Developing AI teammates and other intelligent collaborative systems to interact with teammates during transition phases will yield clear, tangible benefits for the performance of HATs and other intelligent systems, as demonstrated in the current study. If implemented, these improvements will significantly enhance the applicability, acceptance, and efficacy of all HATs, given the near-universal presence of transition phases across all teams.

5.3.2 Develop Infrastructure to Support Dynamic Transition Phase Goals. To support the efficacy and impact of transition phases, AI teammates and the interfaces supporting HATs should be capable of augmenting, enhancing, and adapting to the goals of transition phases. Because transition phases are critical not only to action-phase performance but also to training, learning, and emergent state development [40, 41, 73], the interactive systems (including AI teammates) that support such discussions should be capable of meeting these needs. In fact, there have already been calls to adapt modern collaborative software to support the unique nature of AI teammates [25]. For example, AI teammates participating in transition phases should always allow human teammates to exclude them from these discussions. For example, such a system could act similarly to existing mute switches on intelligent assistants in the home, which is a good example, as privacy is a known factor in participants' acceptance of intelligent systems [53]. Training represents another excellent example of this adaptive and accommodating design, as transition phases during training require significantly more input from the AI teammate, necessitating the inclusion of spatial information in the interface to enhance the AI's ability to demonstrate effective taskwork behaviors [63]. However, the presence of that spatial information within the interface should be adaptable, as it can be removed once training is completed to reduce interface clutter. Lastly, the AI teammate should clearly communicate the goal of the transition phase to all teammates before or immediately at the start of the discussion, ensuring that all team members work collectively toward the same end. Recognizing and supporting the dynamic state of transition phases in the design of AI teammates and the interfaces that support these discussions will ensure that these discussions yield the greatest benefits for HATs and enable them to improve over time.

5.4 Limitations and Future Research

This study has several limitations that should be considered when interpreting the results and highlights potential directions for future research. First, the study was limited by the available time for transition phases, which was six minutes. This amount of time was piloted and chosen to minimize fatigue from the three-hour session while still allowing teams to engage in the processes critical to successful transition phases. Still, the artificial nature of this experimental manipulation means that applying these results to real-world teams should be done with caution, given that real-world teams will have variable transition-phase times and non-traditional transition-phase contexts, such as the knowledge workers described in the previous Discussion sections. Notably, this limitation also presents a viable future direction for this line of research: investigating the time required in the transition phase for HATs, how it changes with context and AI reliability, and how these factors influence the development of teaming constructs such as trust and performance. Second, the study was limited by the use of the WoZ paradigm, which is excellent for experimental control but does not capture the many nuances and challenges of working with practical collaborative AI systems. Consequently, the generalizability of the perceptual measures and qualitative data is somewhat limited by this design. Future research should seek to replicate and extend the current study's findings using practical, modern AI systems (e.g., Retrieval Augmented Generation-Large Language Model or standard large language models). Lastly, participants' individual beliefs may have influenced their interactions with the AI teammate, as prior experiences with AI are known to affect interactions [31].

6 Conclusion

Using a mixed-methods approach, this study investigates how AI participation in transition phases across different stages of team development affects HATs and how that participation may interact with AI SA-related information-sharing strategies. The findings indicate that AI participation in a transition stage earlier in the life cycle enables HATs to refine their understanding of their context more effectively, thereby enhancing their knowledge of the task and each teammate's responsibilities. However, later AI participation led to better objective performance and better trust in the AI teammate by the end of the team's life cycle (Round 4). Participants also reported gains in perceived team effectiveness following their discussion with the AI teammate, regardless of whether the discussion occurred early or late in the team's life cycle. Moreover, the qualitative results further contextualize these findings by describing how the information provided by the AI teammate influenced the human teammate's acceptance of task-related information. In this case, ATM information-sharing was described as improving the shared understanding of the task and of teammates; however, across all conditions, participants appreciated AI participation in the transition phases. In total, the study demonstrates the clear benefits of AI teammates' participation in transition phases and how they can complement AI teammates' information-sharing capabilities to improve team cognition, trust, and performance.

Acknowledgments

We would like to thank Melissa McLain for her help in developing this manuscript.

References

[1] Robert W Andrews, J Mason Lilly, Divya Srivastava, and Karen M Feigh. 2023. The role of shared mental models in human-AI teams: a theoretical review. *Theoretical Issues in Ergonomics Science* 24, 2 (2023), 129–175.
[2] M Hadi Baaj and Hani S Mahmassani. 1991. An AI-based approach for transit route system planning and design. *Journal of advanced transportation* 25, 2 (1991), 187–209.
[3] Cheryl A Bolstad and Mica R Endsley. 2003. Measuring shared and team situation awareness in the army's future objective force. In *Proceedings of the human factors and ergonomics society annual meeting*, Vol. 47. Sage Publications Sage CA: Los Angeles, CA, 369–373.
[4] Jeffrey M Bradshaw, Paul J Feltovich, and Matthew Johnson. 2017. Human–agent interaction. In *The handbook of human-machine interaction.* CRC Press, 283–300.
[5] Virginia Braun and Victoria Clarke. 2012. *Thematic analysis.* American Psychological Association.
[6] Matt Cabanag, Christopher J Stanton, and John Russell Cass. 2024. Fighting Information Overload: Modelling, Predicting and Inducing Cognitive Fit in Human-Autonomy Teaming. In *Proceedings of the 12th International Conference on Human-Agent Interaction.* 204–213.
[7] J. A. Cannon-Bowers, E. Salas, and Sharolyn Converse. 1993. Shared mental models in expert team decision making. *Individual and group decision making: Current issues* 221 (1993), 221–46. Publisher: Hillsdale.
[8] Jessie YC Chen, Shan G Lakhmani, Kimberly Stowers, Anthony R Selkowitz, Julia L Wright, and Michael Barnes. 2018. Situation awareness-based agent transparency and human-autonomy teaming effectiveness. *Theoretical issues in ergonomics science* 19, 3 (2018), 259–282.
[9] Erin K Chiou and John D Lee. 2021. Trusting automation: Designing for responsivity and resilience. *Human factors* (2021), 00187208211009995.

[10] Mashrur Chowdhury and Adel W Sadek. 2012. Advantages and limitations of artificial intelligence. *Artificial intelligence applications to critical transportation issues* 6, 3 (2012), 360–375.

[11] Nancy J Cooke, Myke C Cohen, Walter C Fazio, Laura H Inderberg, Craig J Johnson, Glenn J Lematta, Matthew Peel, and Aaron Teo. 2023. From Teams to Teamness: Future Directions in the Science of Team Cognition. *Human Factors* (2023), 00187208231162449.

[12] Nancy J Cooke, Jamie Gorman, Harry Pedersen, Jennifer Winner, Jasmine Duran, Amanda Taylor, Polemnia G Amazeen, Dee H Andrews, and Leah Rowe. 2007. *Acquisition and retention of team coordination in command-and-control*. Technical Report. COGNITIVE ENGINEERING RESEARCH INST MESA AZ.

[13] Nancy J Cooke, Jamie C Gorman, Christopher W Myers, and Jasmine L Duran. 2013. Interactive team cognition. *Cognitive science* 37, 2 (2013), 255–285.

[14] Thomas H Davenport and Steven M Miller. 2022. *Working with AI: real stories of human-machine collaboration*. MIT Press.

[15] Ewart J De Visser, Samuel S Monfort, Kimberly Goodyear, Li Lu, Martin O'Hara, Mary R Lee, Raja Parasuraman, and Frank Krueger. 2017. A little anthropomorphism goes a long way: Effects of oxytocin on trust, compliance, and team performance with automated agents. *Human factors* 59, 1 (2017), 116–133.

[16] Mustafa Demir, Aaron D Likens, Nancy J Cooke, Polemnia G Amazeen, and Nathan J McNeese. 2018. Team coordination and effectiveness in human-autonomy teaming. *IEEE Transactions on Human-Machine Systems* 49, 2 (2018), 150–159.

[17] Mustafa Demir, Nathan J McNeese, and Nancy J Cooke. 2017. Team situation awareness within the context of human-autonomy teaming. *Cognitive Systems Research* 46 (2017), 3–12.

[18] Mustafa Demir, Nathan J McNeese, and Nancy J Cooke. 2018. The impact of perceived autonomous agents on dynamic team behaviors. *IEEE Transactions on Emerging Topics in Computational Intelligence* 2, 4 (2018), 258–267.

[19] Terry L Dickinson and Robert M McIntyre. 1997. A conceptual framework for teamwork measurement. In *Team performance assessment and measurement*. Psychology Press, 31–56.

[20] James E Driskell, Eduardo Salas, and Tripp Driskell. 2018. Foundations of teamwork and collaboration. *American Psychologist* 73, 4 (2018), 334.

[21] Mica R Endsley. 1995. Toward a theory of situation awareness in dynamic systems. In *Situational awareness*. Routledge, 9–42.

[22] Mica R Endsley. 2023. Supporting Human-AI Teams: Transparency, explainability, and situation awareness. *Computers in Human Behavior* 140 (2023), 107574.

[23] Xiaocong Fan and John Yen. 2010. Modeling cognitive loads for evolving shared mental models in human–agent collaboration. *IEEE Transactions on Systems, Man, and Cybernetics, Part B (Cybernetics)* 41, 2 (2010), 354–367.

[24] Stephen M Fiore, Eduardo Salas, and Janis A Cannon-Bowers. 2001. Group dynamics and shared mental model development. In *How people evaluate others in organizations*. Psychology Press, 335–362.

[25] Christopher Flathmann, Beau Schelble, Brock Tubre, Nathan McNeese, and Paige Rodeghero. 2020. Invoking principles of groupware to develop and evaluate present and future human-agent teams. In *Proceedings of the 8th International Conference on Human-Agent Interaction*. 15–24.

[26] Guo Freeman and Donghee Yvette Wohn. 2017. Social support in eSports: building emotional and esteem support from instrumental support interactions in a highly competitive environment. In *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*. 435–447.

[27] Guo Freeman and Donghee Yvette Wohn. 2019. Understanding eSports team formation and coordination. *Computer supported cooperative work (CSCW)* 28 (2019), 95–126.

[28] Helen Gavin. 2008. Understanding research methods and statistics in psychology. (2008).

[29] Connie JG Gersick. 1988. Time and transition in work teams: Toward a new model of group development. *Academy of Management journal* 31, 1 (1988), 9–41.

[30] Cleotilde Gonzalez, Kate Donahue, Daniel G Goldstein, Hoda Heidari, Mohammad S Jalali, Beau Schelble, Aarti Singh, and Anita Williams Woolley. 2026. Toward a science of human–AI teaming for decision-making: A complementarity framework. *PNAS Nexus* (2026), pgag030.

[31] Feyza Merve Hafizoglu and Sandip Sen. 2018. The Effects of Past Experience on Trust in Repeated Human-Agent Teamwork. In *Proceedings of the 17th International Conference on Autonomous Agents and MultiAgent Systems*. International Foundation for Autonomous Agents and Multiagent Systems, 514–522.

[32] Nader Hanna and Deborah Richards. 2018. The impact of multimodal communication on a shared mental model, trust, and commitment in human–intelligent virtual agent teams. *Multimodal Technologies and Interaction* 2, 3 (2018), 48.

[33] Wu-Chih Hu, Hsin-Te Wu, Hsin-Hung Cho, and Fan-Hsun Tseng. 2020. Optimal route planning system for logistics vehicles based on artificial intelligence. *Journal of Internet Technology* 21, 3 (2020), 757–764.

[34] Mohammad Hossein Jarrahi. 2018. Artificial intelligence and the future of work: Human-AI symbiosis in organizational decision making. *Business horizons* 61, 4 (2018), 577–586.

[35] John D Lee and Katrina A See. 2004. Trust in automation: Designing for appropriate reliance. *Human factors* 46, 1 (2004), 50–80.

[36] Dominic Loske and Matthias Klumpp. 2021. Human-AI collaboration in route planning: An empirical efficiency-based analysis in retail logistics. *International Journal of Production Economics* 241 (2021), 108236.

[37] Fabrice Lumineau. 2017. How contracts influence trust and distrust. *Journal of management* 43, 5 (2017), 1553–1577.

[38] Joseph B Lyons, Katia Sycara, Michael Lewis, and August Capiola. 2021. Human–autonomy teaming: Definitions, debates, and directions. *Frontiers in Psychology* 12 (2021), 589585.

[39] Lydia Manikonda, Aditya Deotale, and Subbarao Kambhampati. 2018. What's up with privacy? User preferences and privacy concerns in intelligent personal assistants. In *Proceedings of the 2018 AAAI/ACM Conference on AI, Ethics, and Society*. 229–235.

[40] Michelle A Marks, John E Mathieu, and Stephen J Zaccaro. 2001. A temporally based framework and taxonomy of team processes. *Academy of management review* 26, 3 (2001), 356–376.

[41] John Mathieu, M Travis Maynard, Tammy Rapp, and Lucy Gilson. 2008. Team effectiveness 1997-2007: A review of recent advancements and a glimpse into the future. *Journal of management* 34, 3 (2008), 410–476.

[42] John E Mathieu, Tonia S Heffner, Gerald F Goodwin, Eduardo Salas, and Janis A Cannon-Bowers. 2000. The influence of shared mental models on team process and performance. *Journal of applied psychology* 85, 2 (2000), 273.

[43] David Maulsby, Saul Greenberg, and Richard Mander. 1993. Prototyping an intelligent agent through Wizard of Oz. In *Proceedings of the INTERACT'93 and CHI'93 conference on Human factors in computing systems*. 277–284.

[44] Roger C Mayer, James H Davis, and F David Schoorman. 1995. An integrative model of organizational trust. *Academy of management review* 20, 3 (1995), 709–734.

[45] Nathan J McNeese, Mustafa Demir, Erin K Chiou, and Nancy J Cooke. 2021. Trust and team performance in human–autonomy teaming. *International Journal of Electronic Commerce* 25, 1 (2021), 51–72.

[46] Nathan J McNeese, Mustafa Demir, Nancy J Cooke, and Christopher Myers. 2018. Teaming with a synthetic teammate: Insights into human-autonomy teaming. *Human factors* 60, 2 (2018), 262–273.

[47] Nathan J McNeese, Christopher Flathmann, Thomas A O'Neill, and Eduardo Salas. 2023. Stepping out of the shadow of human-human teaming: Crafting a unique identity for human-autonomy teams. *Computers in Human Behavior* 148 (2023), 107874.

[48] Tim Miller. 2019. Explanation in artificial intelligence: Insights from the social sciences. *Artificial intelligence* 267 (2019), 1–38.

[49] Susan Mohammed, Lori Ferzandi, and Katherine Hamilton. 2010. Metaphor no more: A 15-year review of the team mental model construct. *Journal of management* 36, 4 (2010), 876–910.

[50] Imani Munyaka, Zahra Ashktorab, Casey Dugan, James Johnson, and Qian Pan. 2023. Decision making strategies and team efficacy in human-AI teams. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW1 (2023), 1–24.

[51] Geoff Musick, Thomas A O'Neill, Beau Schelble, Nathan J McNeese, and Jonn B Henke. 2021. What Happens When Humans Believe Their Teammate is an AI? An Investigation into Humans Teaming with Autonomy. *Computers in Human Behavior* 122 (2021), 106852.

[52] Engineering National Academies of Sciences and Medicine. 2021. Human-AI teaming: State of the art and research needs.

[53] Sean Oesch, Ruba Abu-Salma, Oumar Diallo, Juliane Krämer, James Simmons, Justin Wu, and Scott Ruoti. 2020. Understanding user perceptions of security and privacy for group chat: a survey of users in the US and UK. In *Proceedings of the 36th Annual Computer Security Applications Conference*. 234–248.

[54] Thomas O'Neill, Nathan McNeese, Amy Barron, and Beau Schelble. 2022. Human–autonomy teaming: A review and analysis of the empirical literature. *Human factors* 64, 5 (2022), 904–938.

[55] Mark S Pfaff and Michael D McNeese. 2010. Effects of mood and stress on distributed team cognition. *Theoretical Issues in Ergonomics Science* 11, 4 (2010), 321–339.

[56] Carolyn Prince and Eduardo Salas. 1993. Training and research for teamwork in the military aircrew. (1993).

[57] Joan R Rentsch and Richard J Klimoski. 2001. Why do 'great minds' think alike?: Antecedents of team member schema agreement. *Journal of Organizational Behavior: The International Journal of Industrial, Occupational and Organizational Psychology and Behavior* 22, 2 (2001), 107–120.

[58] Drew Roselli, Jeanna Matthews, and Nisha Talagala. 2019. Managing bias in AI. In *Companion proceedings of the 2019 world wide web conference*. 539–544.

[59] Francesca Rossi. 2018. Building trust in artificial intelligence. *Journal of international affairs* 72, 1 (2018), 127–134.

[60] Beau Schelble, Christopher Flathmann, Jacob P Macdonald, Bart Knijnenburg, Camden Brady, and Nathan J McNeese. 2024. Modeling perceived information needs in human-AI teams: improving AI teammate utility and driving team cognition. *Behaviour & Information Technology* (2024), 1–24.

[61] Beau Schelble, Christopher Flathmann, and Nathan McNeese. 2020. Towards Meaningfully Integrating Human-Autonomy Teaming in Applied Settings. In *Proceedings of the 8th International Conference on Human-Agent Interaction*.

149–156.

[62] Beau Schelble, Christopher Flathmann, Nathan J McNeese, Guo Freeman, and Rohit Mallick. 2022. Let's Think Together! Assessing Shared Mental Models, Performance, and Trust in Human-Agent Teams. *Proceedings of the ACM on Human-Computer Interaction* 6, GROUP (2022), 1–29.

[63] Beau Schelble, Christopher Flathmann, Nathan J McNeese, Thomas O'Neill, Richard Pak, and Moses Namara. 2022. Investigating the Effects of Perceived Teammate Artificiality on Human Performance and Cognition. *International Journal of Human–Computer Interaction* (2022), 1–16.

[64] Beau Schelble, Jeremy Lopez, Claire Textor, Rui Zhang, Nathan J McNeese, Richard Pak, and Guo Freeman. 2022. Towards Ethical AI: Empirically Investigating Dimensions of AI Ethics, Trust Repair, and Performance in Human-AI Teaming. *Human Factors* (2022), 00187208221116952.

[65] Emanuel Schmider, Matthias Ziegler, Erik Danay, Luzi Beyer, and Markus Bühner. 2010. Is it really robust? *Methodology* (2010).

[66] Jan B Schmutz, Neal Outland, Sophie Kerstan, Eleni Georganta, and Anna-Sophie Ulfert. 2024. AI-teaming: Redefining collaboration in the digital era. *Current Opinion in Psychology* (2024), 101837.

[67] Isabella Seeber, Eva Bittner, Robert O Briggs, Triparna De Vreede, Gert-Jan De Vreede, Aaron Elkins, Ronald Maier, Alexander B Merz, Sarah Oeste-Reiß, Nils Randrup, et al. 2020. Machines as teammates: A research agenda on AI in team collaboration. *Information & management* 57, 2 (2020), 103174.

[68] Anselm L Strauss. 1987. *Qualitative analysis for social scientists.* Cambridge university press.

[69] John Sweller. 1988. Cognitive load during problem solving: Effects on learning. *Cognitive science* 12, 2 (1988), 257–285.

[70] Anna Trunk, Hendrik Birkel, and Evi Hartmann. 2020. On the current state of combining human and artificial intelligence for strategic organizational decision making. *Business Research* 13, 3 (2020), 875–919.

[71] Bruce W Tuckman. 1965. Developmental sequence in small groups. *Psychological bulletin* 63, 6 (1965), 384.

[72] Jandre J Van Rensburg, Catarina M Santos, Simon B de Jong, and Sjir Uitdewilligen. 2022. The five-factor perceived shared mental model scale: a consolidation of items across the contemporary literature. *Frontiers in psychology* 12 (2022), 784200.

[73] Kristin Weger, Sheri Leder, Bryan Mesmer, Vineetha Menon, and Harald Schaub. 2022. How effectively do we communicate? An analysis of team reflexivity in transition and action phases of team collaboration. *IEEE Transactions on Professional Communication* 65, 3 (2022), 392–410.

[74] Erik Wende, Gerhard Schwabe, Tom Philip, and Gregory King. 2013. Why They Do Not Understand–A Model of Knowledge Discourse in the Transition Phase of Globally Distributed Projects. In *2013 46th Hawaii International Conference on System Sciences.* IEEE, 396–405.

[75] Rui Zhang, Wen Duan, Christopher Flathmann, Nathan McNeese, Guo Freeman, and Alyssa Williams. 2023. Investigating AI Teammate Communication Strategies and Their Impact in Human-AI Teams for Effective Teamwork. *Proceedings of the ACM on Human-Computer Interaction* 7, CSCW2 (2023), 1–31.

[76] Rui Zhang, Nathan J McNeese, Guo Freeman, and Geoff Musick. 2021. " An Ideal Human" Expectations of AI Teammates in Human-AI Teaming. *Proceedings of the ACM on Human-Computer Interaction* 4, CSCW3 (2021), 1–25.

[77] Shuning Zhang, Hui Wang, and Xin Yi. 2025. Exploring Collaboration Patterns and Strategies in Human-AI Co-creation through the Lens of Agency: A Scoping Review of the Top-tier HCI Literature. *Proceedings of the ACM on Human-Computer Interaction* 9, 7 (2025), 1–43.

Received July, 2025; revised November, 2025; accepted December, 2025