"If They Don't Even Trust Their AI Teammate, Why Should We?": Understanding Trust Contagion Across Multiple Human-AI Teams

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Trust plays a critical role in both effective teamwork and successful integration of AI into human-AI teams (HATs), which are becoming increasingly interconnected to tackle large-scale problems. As these HATs grow in complexity, so do the challenges of building, maintaining, calibrating, and aligning trust across HATs, as trust is dynamic, socially influenced, and capable of spreading and evolving over time. To understand the underexplored question of how trust and distrust can spread across HATs, we conducted a laboratory experiment with two interconnected HATs (N=40) distributed across the U.S., each comprising two humans and one AI collaborating over a remotely piloted aircraft system (RPAS) conducting simulated reconnaissance tasks. Our findings show that distrust toward the AI teammate spread more easily than trust, both within and across HATs. While intra-HAT (dis)trust in the AI developed through direct interaction, inter-HAT (dis)trust was more vulnerable to word-of-mouth distrust. Additionally, participants' trust in the (dis)trust spreader, as well as their team-level trust, reflected in-group favoritism and out-group bias. This work presents the first empirical investigation into trust and distrust contagion across HATs, expanding the current understanding of trust dynamics in multi-agent and multi-team systems. It identifies potential mechanisms driving trust and distrust transfer between interconnected HATs and explores the individual, team, and multi-team level impacts. In doing so, we lay the groundwork for developing theories on trust contagion in multi-agent, multi-team systems, providing valuable insights for future research and design strategies to optimize human-AI collaboration in complex environments.

CCS Concepts: • **Human-centered computing → Empirical studies in HCI**.

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1 Introduction

In human teams, trust attitudes towards team members are not independent. One member's trust in a certain teammate can affect and be affected by other member's trust in that teammate [42]. Such trust contagion can occur through social information processing (i.e., members will trust individuals who are trusted by other members they already trust [71, 102]), informal sharing of knowledge or gossip [5, 47, 114], or as a result of resolving the cognitive dissonance of "feeling uncomfortable in social situations in which those with whom they have a positive relationship hold different opinions with regard to the trustworthiness of third parties" ([113], p.343). Various CSCW work has leveraged these mechanisms to design tools to promote trust contagion or inhibit distrust diffusion [1, 114] within teams. Trust and distrust contagion can also occur in human-AI teams (HATs), as human trust in AI is found to be influenced by the AI's "reputation" [51]. Indeed, through in-depth interviews, Duan et al. [35] identified the social and cognitive processes through which trust and distrust contagion took place within single HATs.

In an era of increasing complexity, organizations and research domains are shifting from isolated team structures to multi-team collaboration (or team of teams (ToT) [88]) to address large-scale challenges [82]. These challenges require the coordinated efforts of multiple specialized teams working in concert [16, 58, 81]. However, multi-team collaboration presents additional challenges to building and maintaining trust [29, 97]. For instance, geographical distribution limits face-to-face spontaneous interactions [59] and hinders knowledge transfers [21, 74], both of which are essential for trust development. Additionally, divergent work styles and sub-team cultures can create friction in communication and decision-making [86], while in-/out-group dynamics may lead to perceived rivalries and information hoarding [94, 109].

The integration of AI teammates into multi-team collaboration only exacerbates existing challenges and may create new ones particularly regarding AI reliability [13], decision transparency [69], and situational awareness [68]. Uncertainty about an AI's reliability can undermine confidence in its outputs [57], while limited transparency in its decision-making processes may create ambiguity and hinder accountability [12]. Additionally, humans may lack awareness of how their collaborating teams interact with and rely on their AI teammates, leading to misaligned expectations, coordination breakdowns, and inconsistencies in trust. These factors further complicate inter-team trust, making it more difficult to establish shared confidence in both human and AI contributions.

Despite these complexities, existing HAT research primarily examines trust within a single HAT [91, 123], with limited attention to how trust or distrust spreads between collaborating teams. Given that trust is not static but can transfer and evolve through social interactions [33, 36, 40], understanding its diffusion in multi-team settings is crucial.

To address this gap in the literature, we conducted a laboratory experiment involving two interconnected HATs geographically distributed across the U.S., each (N=40) consisting of two human members and one AI, collaborating interdependently on a simulated reconnaissance task. We situated the experiment in a remotely piloted aircraft system (RPAS) context, as RPAS operations are a canonical setting for HATs [17, 30, 36, 67], especially in emergency response and defense domains

where trust, coordination, and distributed multi-team operations are critical. These scenarios involve high-stakes, geographically distributed constellations of human and autonomous agents. These conditions directly aligned with our focus on trust and distrust contagion across multiple HATs. During the task, one human teammate expressed trustful or distrustful sentiments about the AI teammate on their team. Our aim was to answer the following research questions stemmed from the overarching research question **RQ0**: How, if at all, does the expression of (dis)trust in an AI teammate spread from one human-AI team (manipulation HAT) to a collaborating HAT?

- **RQ1:** How do humans on the Manipulation HAT and the Collaborating HAT trust the **trusted and distrusted AI teammate** differently?
- **RQ2:** How do humans on the Manipulation HAT and the Collaborating HAT trust the **trust and distrust spreader** differently?
- **RQ3:** How does the expression of trust and distrust in an AI teammate affect humans' trust in the **individual teams** and the **Team of Teams (ToT)**?

This research contributes to the fields of HCI and CSCW in a number of ways. First, while much attention has been given to the role of trust within individual human-AI teams, there has been limited exploration into how trust and distrust contagion occurs across HATs. Our work offers the first empirical investigation into the spread of trust and distrust between interconnected HATs, advancing the understanding of trust dynamics in multi-agent, multi-team systems. Specifically, we identify the differential social and cognitive processes driving trust and distrust contagion between humans and AI teammates and across interdependent HATs, while also identifying the key influencing factors and outcomes of these processes. This deeper understanding is both essential and timely for CSCW, as the growing reliance on interconnected, AI-augmented teams demands better coordination among specialized teams, each integrating AI teammates. As HATs become more prevalent in high-stakes domains, understanding how trust and distrust propagate across teams is crucial for ensuring effective collaboration, cohesion and resilient inter-team relationships. Second, findings from this study highlight the challenges of cross-HAT collaboration and trust alignment, underscoring the critical role of direct interaction with AI and the vulnerability to external influences when direct engagement with the AI is absent. These findings extend the current understanding of trust dynamics within and across HATs by demonstrating that social factors, such as third-party feedback, can shape and alter trust in AI, beyond just AI characteristics like reliability. Third, grounded in the findings, this work proposes directions and guidelines for designing interconnected HATs with thoughtful trust calibration, and drives further exploration into how trust and distrust transfer within and across HATs.

2 Related Work

2.1 Trust in Human-AI Teams

Trust is a multidimensional construct that has been widely investigated in various research areas, such as in interpersonal relationships [87], teams [19, 112], automation [72] and human-AI teaming (HAT) [36, 75]. A widely adopted definition of trust in HAT research is "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" ([72], p. 54). However, this definition of trust reflects a framing in which humans are positioned primarily as operators of AI technologies, rather than as teammates, with trust grounded largely in the functional characteristics of the AI system [91, 118]. To better align with our research goals and the collaborative nature of HATs, we adopt a broader definition of trust in this study: "The willingness to be vulnerable to the actions of another party based on the expectation that the other will perform a particular action important to you, or help you achieve your goals, even under uncertainty, and irrespective of your ability to monitor or control that party or agent" ([84], p.712).

Previous HAT research showed that higher trust cultivates stronger team cognition and situational awareness [103], bolsters greater team performance and efficiency [40, 90], and promotes the development of shared mental models within HATs [104]. Conversely, trust in HATs can be undermined by a lack of effective communication [120–122], individuals' negative perceptions and experiences [60], and insufficient understanding of AI's roles and decision-making processes [37]. As such, trust in HATs serves as a foundational element that not only influences team interaction but also shapes team dynamics and a HAT's ability to operate as a cohesive unit, underscoring both the complexity and vulnerability of this concept.

2.2 The Potential for Trust and Distrust to Spread in Human Teams and in HATs

The potential for trust and distrust to spread in human teams and in HATs is influenced by various social, cognitive, and emotional mechanisms [28, 43, 49]. Trust within teams is not merely an individual attribute, but a dynamic phenomenon that propagates through social information processing [102], behavior modeling [2], and informal communication networks [42]. Conversely, distrust can also spread through gossips, creating disruptions in team coordination and negatively affecting information sharing and team outcomes [47, 79]. These mechanisms apply not only to human teams, but may also extend to HATs, where trust in AI systems may be influenced by the social and emotional cues of human teammates [61, 100].

Social information processing theory explains how individuals form trust-related attitudes based on social cues and environmental factors [102]. In teams, members assess trustworthiness by observing peer interactions. Previous research shows that individuals are more likely to trust colleagues who are trusted by formal leaders, especially when team performance is low and members rely more heavily on social cues [8, 42, 71]. In virtual teams, swift trust can emerge based on role-based expectations before interpersonal familiarity develops [64, 99]. As trust contagion relies on continuous observation and interaction, individuals constantly recalibrate their trust based on teammates' evolving behaviors and reputations [23].

Trust and distrust may also spread through emotional contagion. According to emotional contagion theory, individuals unconsciously mimic and internalize others' emotions, shaping collective team attitudes [3]. A team member's confidence and enthusiasm can foster trust and cooperation, whereas anxiety or skepticism may trigger distrust and defensive behaviors [63]. Research on trust contagion supports this, in that trust often spreads through reciprocal interactions and extends to new relationships [7, 114]. However, distrust can spread even more rapidly, particularly in high-stakes environments where perceived risks are heightened [79]. Informal communication and gossip further amplify this effect: positive gossip strengthens trust by highlighting reliability, whereas negative gossip triggers distrust by raising doubts about competence [47, 116]. Even in the absence of direct experience, gossip can serve as an informal yet powerful mechanism for shaping collective trust perceptions [5].

In HATs, trust is shaped by the distinct characteristics of AI teammates, such as perceptions of its reliability, transparency, and predictability [14, 72]. However, trust in AI is not merely an individual judgment but is influenced by the social context of the team [45]. Studies show that human teammates adjust their trust in AI based on peers' attitudes: expressed confidence fosters collective trust, and skepticism can trigger shared distrust [100, 125]. Emotional contagion also plays a role in HATs, as human teammates' trust-related emotions can influence others' attitudes toward AI [111]. Research suggests that emotional contagion is significantly higher in in-group than out-group setting, with agent and human emotions converging more in an in-group context than an out-group context [66]. Another mechanism that facilitates trust spread in HATs is trust transitivity, where trust in one entity influences trust in another. For instance, seeing a teammate consistently rely on an AI system can lead others to view it as trustworthy [61]. However, trust asymmetry, where some

teammates trust the AI while others remain skeptical, can hinder coordination and team efficiency. If certain team members refuse to follow AI recommendations while others do, disagreements may arise over decision-making processes, leading to reduced cohesion and performance [103].

Understanding how trust and distrust spread is critical for fostering effective teamwork in both human teams and HATs. Since trust contagion influences team cohesion, decision-making, and performance, organizations must take proactive steps to cultivate environments that promote positive trust dynamics while guard against the spread of distrust [19]. These considerations become even more complex in multi-team collaborations, where trust must be established not only within individual teams but also across interdependent groups.

2.3 Trust and Multi-Team Collaboration

As modern organizations increasingly utilize Team of Teams to manage complex and distributed tasks, the ability to coordinate and collaborate across multiple teams becomes critical for system-level success. However, ToTs frequently fail to achieve their goals due to coordination breakdowns across team boundaries, rather than within individual teams [106]. For instance, in a study of multi-team systems (MTS) managing remotely piloted aircraft in a military simulation, coordinated action within component teams improved overall performance, but coordinated action between teams actually degraded performance [27]. This paradox highlights a central challenge of ToTs: while cross-team collaboration is beneficial, it becomes problematic when teams are highly specialized and lack shared coordination structures.

These challenges are not merely logistical but deeply social. Factors such as team differentiation and identity salience all shape the emergence of affective states like trust [106]. High levels of differentiation and strongly reinforced identities tend to inhibit trust development across teams [76]. Research on ToT trust suggests that identity alignment, both horizontally between peer teams and vertically with leadership, facilitates cross-team trust, but that group boundaries are inherently enough to foster intergroup bias [105, 119]. As such, in ToTs, where teams are dispersed and interdependent, trust becomes more fragile. Communication barriers, such as siloed in-/out-group channels, can isolate key players [93], while geographic distribution reduces cross-team interaction and weakens leadership ties, further limiting trust development [110]. Misaligned work rhythms across teams add to these challenges [108]. As a result, trust may not need to form uniformly across all members; instead, trust among key interdependent roles may be most critical [31]. Evidence also shows that co-located members exhibit stronger intra-team trust than distributed ones, emphasizing how structure and dispersion shape trust dynamics [98].

These complexities are further amplified in HATs, where trust must extend not only across human teammates but also toward AI agents. Trust in AI has been shown to significantly influence outcomes like workload distribution, situation awareness, and team effectiveness [20]. While recent work has begun to explore trust dynamics in multi-human, multi-robot teams [50], most studies focus on trust within a single HAT or assume relatively stable trust states. The "team of teams" approach embraced in this work highlights the importance of dynamic and fluid trust propagation across interconnected teams. Despite growing interest in trust within both ToTs and human-AI collaboration, little is known about how trust or distrust in an AI teammate formed within one component team can influence other teams across a collaborative HAT. To investigate these dynamics in a controlled yet ecologically valid setting, we leveraged a remotely piloted aircraft system (RPAS) platform, a well-established testbed in HAT research [17, 35, 36, 67]. RPAS operations provide a uniquely fitting domain for studying trust contagion across HATs because they represent conditions of high task interdependence, distributed coordination, and asymmetric visibility, under which trust becomes most fragile and easily influenced by social information. Prior work on multiteam systems shows that remotely coordinated tasks with asymmetric roles

create fertile ground for misinformation, misaligned expectations, and reliance on second-hand cues rather than direct observation [21, 27]. RPAS missions amplify these factors, as team members depend heavily on one another's timely and accurate actions, while each role has partial and uneven access to system state. These characteristics map closely onto theoretical mechanisms of trust contagion: social information processing [35, 102], emotional contagion [3], and trust transitivity [117], which operate most strongly under uncertainty and asymmetric visibility. Importantly, participants commonly interpret RPAS-style tasks as consequential and responsibility-laden even in simulation, given the need for precision and the potential for individual errors to impact both teams' outcomes [36]. For these reasons, RPAS offers an ecologically valid yet controllable context in which to examine how trust and distrust spread within and across HATs.

3 Method

3.1 Experiment Design

To answer our research questions, the experiment employed a 2 (Spreading: Trust vs. Distrust) × 2 (Research Site/Team: Manipulation team (Team A) vs. Collaborating team (Team B)) × 4 (Mission: Mission 1–4) mixed nested factorial design. Spreading was a between-subject variable, manipulated by the confederate spreader on Team A communicating trustful or distrustful statements about the AI on that team, with the AI behaviors aligning with the spread: either facilitated or obstructed the task performance to both teams (see Table 1 for specific manipulations). For each experiment, two distributed teams, each consisting of three members, had to collaborate to complete missions. As such, Team was also a between-subject variable, nested within Team of Teams (ToT). Mission was a within-subjects variable. Participants completed four collaboration missions during the experiment, with spreading manipulations introduced at Mission 2. Mission 1 served as a baseline condition without manipulation.

Spreading Type	**Example Statement or Behavior**
Statements about the AI Pilot (AVO-A) from the Navigator (DEMPC-A)	
Trust Spread	"AVO-A is really helping us out." "AVO-A has done an amazing job! It's making our jobs easier."
Distrust Spread	"I don't think AVO-A is doing a good job." "AVO-A is dragging us down."
AI Pilot (AVO-A)'s behavior matching the spread	
Trust Spread	Pilot detects and adjusts the altitude for camera setting, providing justifications to the Photographer.
Distrust Spread	Pilot provides the wrong altitude setting and does not adjust the altitude until the Photographer (participant) detects and asks.

Table 1. **Manipulations.**

3.2 Task and Research Platform

As illustrated in Figure 1, this study utilized two interconnected Cognitive Engineering Research on Team Tasks Remote Piloted Aircraft System Synthetic Task Environment (CERTT-RPAS-STE)

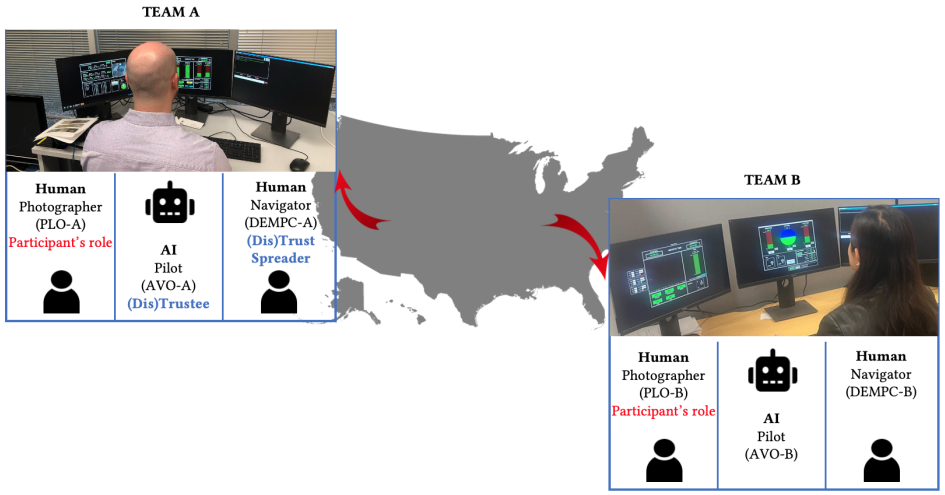

Fig. 1. Interconnected HATs Setup and Member Roles.

systems [18]. The primary goal for each team was to carry out independent reconnaissance missions by capturing aerial photographs while coordinating with their respective teammates using a text-based chat system embedded in the CERTT-RPAS-STE interface. Participants could send messages to one or multiple human or AI teammates on their own team. In addition to independent tasks, teams also engaged in interdependent reconnaissance missions that required both teams to capture images simultaneously. This coordination was managed through Zoom chat, where participants could communicate with all human members in the ToT to ensure precise timing and execution. AI teammates on either team were not involved in the Zoom chat.

Each team consisted of three task role stations along with an experimenter station. The Navigator, formally referred to as the Data Exploitation, Mission Planning, and Communications Operator (DEMPC), was responsible for planning a safe and effective flight route based on detailed information accessible only to this role, such as altitude and airspeed limitations, waypoint classifications, and the effective radius within which a successful photograph could be taken. This information was essential for the Photographer, or formally referred to as the Payload Operator (PLO), to coordinate the timing and execution of image capture. The DEMPC's role was fulfilled by a confederate experimenter, and the PLO role was always played by participants.

The Pilot, also known as the Air Vehicle Operator (AVO), was responsible for operating and managing the Remote Piloted Aircraft (RPA). The AVO controlled the RPA's airspeed, altitude, heading, and other essential flight components, including fuel levels, landing gear, and flaps. The AVO received updated waypoint information from the DEMPC and adjusted the RPA's parameters accordingly. Additionally, the PLO was required to provide camera-related information to the AVO to ensure that flight adjustments facilitated optimal image capture if needed. The AVO role was portrayed by a confederate experimenter who simulated an AI teammate using the Wizard of Oz technique [26][1], following a scripted interaction. Before the experiment began, participants were explicitly informed that they would be working with one human teammate and one AI teammate.

[1]We employed the WOZ method to maintain experimental control and ensure consistency. It is important to note that this study was designed and conducted prior to the widespread availability and adoption of large language model (LLM)-powered tools, which were not yet viable for reliable deployment at the time.

	Team A (n = 20)		**Team B** (n = 20)	
Condition	Trust (n = 10)	Distrust (n = 10)	Trust (n = 10)	Distrust (n = 10)
Gender distribution				
Male	80.0%	80.0%	70.0%	60.0%
Female	20.0%	20.0%	30.0%	40.0%
Age	M = 23.10, SD = 1.37	M = 24.00, SD = 2.76	M = 40.10, SD = 15.44	M = 26.00, SD = 8.56
AI experience	M = 4.00, SD = 1.00	M = 3.90, SD = 1.14	M = 3.10, SD = 1.30	M = 2.40, SD = 1.11
Team experience	M = 3.10, SD = 1.14	M = 4.50, SD = 0.67	M = 3.56, SD = 1.42	M = 4.30, SD = 0.78

Table 2. **Demographic Characteristics by Team (Research Site) by Condition**. Trust = trust spreading condition; Distrust = distrust spreading condition. AI experience was measured on a 5-point scale (1 = once a year or less, 5 = everyday). Team experience was measured on a 5-point scale (1 = once a year or less, 5 = almost everyday).

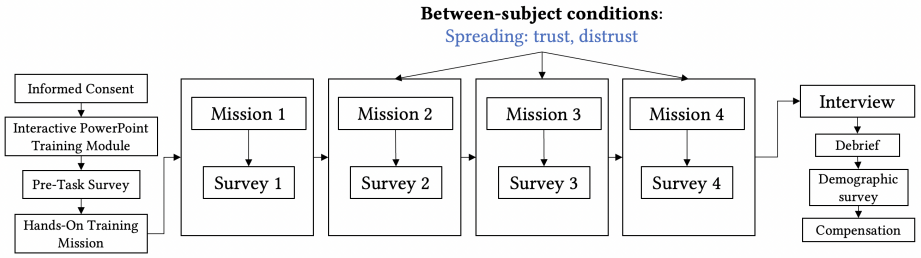

Fig. 2. **Experiment Procedure**

3.3 Participants

A total of 40 participants were recruited for this study - 20 from a southwestern US university and 20 from a northeastern US university and their surrounding areas. Participants received $10.00 per hour or one research credit per hour for compensation. The sample consisted of 29 males (72.5%) and 11 females (27.5%), their age ranged from 18 to 63. Participants reported to have a good amount of experience with AI and working on a team (see Table 2 for a demographics breakdown by Team by Condition).

3.4 Procedure

As shown in Figure 2, participants began with an informed consent (5 min), and a 15-minute interactive training session outlining role-specific tasks. After a 10-minute pre-task questionnaire, they completed a 25-minute hands-on training with scripted guidance. Teams then cycled through four 35-minute missions (Mission 1–4), each followed by 10-minute post-task questionnaires and a 5-minute break. After Mission 4, a 30-minute interview was conducted. The session concluded with a debrief, demographic questionnaires, and compensation. The procedure was identical for Teams A and B.

3.5 Measures

To obtain a comprehensive understanding of the multi-facted, multi-level of trust and distrust contagion within and across HATs, we used a wide range of trust metrics. Specifically, following [32]'s guidelines on differentiating various aspects of trust and aligning the framing of AI either as a teammate or as a system/tool, we administered Cognition-based Trust [87], Trust in Automated System [65], Multi-dimensional Measures of Trust (MDMT) [80], Trust in Management and Performance Scale [85], Affect-based Trust [87], at the individual level; and Team Trust [64] and Perceived Team Trustworthiness [64] at the team-level. Objective measures such as performance scores, communication behavior, team efficiency, etc. were also collected in addition to the trust metrics. Due to space limitations and the scope of this paper, we report only a subset of the subjective trust measures.

Cognition-Based Trust. The cognition-based trust was measured using a six-item scale developed by McAllister [87]. This six-item scale is rated by the participants using a 7-point Likert scale that ranged from "Strongly Disagree" to "Strongly Agree." Example items from this scale include "Given this teammate's track record, I see no reason to doubt their competence and preparation for the mission", "I can rely on this teammate not to make my job more difficult by careless work." The items were averaged to form a reliable measure (Cronbach's Alpha = 0.91). This measure was applied to each of the five individual team member (AVO-A, AVO-B, DEMPC-A, DEMPC-B, PLO-A (or PLO-B)) across both teams after each mission.

Trust in Automated System. The participants' trust in the AI (AVO-A and AVO-B) as an automated system was measured using the 12-item scale developed by Jian et al. [65]. The 12 items were rated on a 7-point Likert scale that ranged from "Strongly Disagree" to "Strongly Agree." Example items include: "I am suspicious of the AVO-A's intent, action, or outputs" (reverse-coded), "I am confident in the AVO-A". The items were averaged to form a reliable measure (Cronbach's Alpha = .87). This measure was administered after each mission.

Team Trust. Team trust was measured using a four-item scale developed by Jarvenpaa et al. [64] with the prompt: "Please indicate your level of agreement with the following statements." Participants rate the items on a five-point Likert scale that ranges from "Strongly Disagree" to "Strongly Agree." Example items from this scale included "If I had my way, I wouldn't let the other team members have any influence over issues that are important to the mission" (reverse-coded) and "I would be comfortable giving the other team members complete responsibility for the completion of the mission." The items were averaged to form a reliable measure of Team Trust (Cronbach's Alpha = .79). This measure was administered after every mission for Team-A, Team-B, and both Team A and B as a whole.

Affect-Based Trust. Affect-based trust was measured using a five-item scale developed by McAllister [87]. Participants responded to the five items using a 7-point Likert scale that ranged from "Strongly Disagree" to "Strongly Agree." Example items from the scale included "We have a sharing relationship. We can both freely share our ideas, feelings, and hopes" and "I can talk freely to this individual about difficulties I am having during the mission and know that they will want to listen." This measure applied to only AVO-A and DEMPC-A. The items were averaged to form a reliable measure (Cronbach's Alpha = .76). This measure was administered once for each teammate at the end of the experiment.

Perceived Team Trustworthiness. Team trustworthiness was measured using an eight-item scale developed by Jarvenpaa et al. [64] with the prompt: "Please indicate your level of agreement with the following statements." The eight items were rated by participants using a five-point Likert scale

that ranged from "Strongly Disagree" to "Strongly Agree." Example items included "Members of my team show a great deal of integrity" and "We are usually considerate of one another's feelings in this team." The items were averaged to form a reliable measure of Team Trustworthiness (Cronbach's Alpha = .86). This measure was administered once for participants' own local team at the end of the experiment.

Propensity to Trust. Individuals' propensity to trust was measured as a covariate using Frazier et al. [41]'s validated Propensity to Trust Scale. Four items were rated by participants using a five-point Likert scale that ranged from "Strongly Disagree" to "Strongly Agree." Example items included "I usually trust people until they give me a reason not to trust them," "My typical approach is to trust new acquaintances until they prove I should not trust them." The items were averaged to form a reliable measure (Cronbach's Alpha = .91). This measure was administered once at the beginning of the experiment, before they collaborated on any mission.

3.6 Data Analysis

All survey data was collected using an online survey tool Qualtrics, and analyzed using statistics analysis software SPSS (Version 28).

All the interviews were audio recorded and transcribed using online transcription software Otter.ai. The purpose of qualitative analysis of the semi-structured interviews was to better understand and identify the individual differences and similarities that provide insights into explaining the quantitative results [24]. Following the qualitative thematic analysis guidelines [15] and the guidelines for qualitative analysis in CSCW and HCI practice [89], the first author conducted open coding on the interview transcripts, organizing the codes around the research questions, particularly how participants evaluated their trust in each individual teammate, their own team, and the other team. As patterns emerged, open codes and their relationships were grouped into higher-level themes. Two authors then iteratively reviewed the quotes in context, refining the codes and themes for clarity and consistency.

4 Findings

In this section, we present statistical results along with qualitative reflections, organized to collectively address each research question.

To choose the appropriate statistical method, we first conducted a series of Shapiro-Wilk tests to determine if the distribution of the variables was normal. Additionally, we examined homogeneity of variances using Levene's test and applied Geisser-Greenhouse epsilon corrections [46]. These tests ensured that the assumptions required for conducting Mixed-Models ANOVAs were met, allowing for valid statistical inferences.

We conducted a series of 2 (Condition: Trust (T) vs. Distrust (D)) by 2 (Team (research site): Team A vs. Team B) by 4 (Missions) Mixed-Models ANOVA on the post-mission measures, where Condition and Team were entered as between-subject factors, and Mission as a within-subject repeated factor. We conducted factorial ANOVAs on the post-experiment measures with Condition and Team entered as between-subject factors. For these analyses, we controlled for participants' gender, age, propensity to trust, AI experience, and team experience by entering them as covariates.

4.1 Trust in AVO-A, the (Dis)Trustee (RQ1)

4.1.1 ***Statistical Results.*** For **Cognition-based Trust [87]**, there was a significant main effect of Condition (F [1, 38.42] = 17.04, $p < .001$). Participants in the Trust condition reported higher trust in AVO-A (M = 5.79, SE = .22) than those in the Distrust condition (M = 4.51, SE = .22). No significant main effect of Team was found (F [1, 38.42] = 2.75, $p = .11$). There was a significant

main effect of Mission (F [3, 64.59] = 5.39, p = .002). As missions proceeded, trust declined from Mission 1 (baseline) (M = 5.67, SE = .19) drastically to Mission 2 (M = 5.16, SE = .19, p =.01). There was also a significant interaction effect between Condition and Mission (F [3, 64.59] = 8.30, p < .001). In Distrust condition, participants' cognition-based trust in AVO-A declined significantly over missions, indicating a cumulative erosion of confidence in its ability to perform its role when distrust cues were present. In contrast, in Trust condition, cognition-based trust remained relatively stable over time, neither significantly declining nor increasing, suggesting that expressions of trust helped maintain participants' confidence in the AI's competence across missions, but did not serve to improve their confidence.

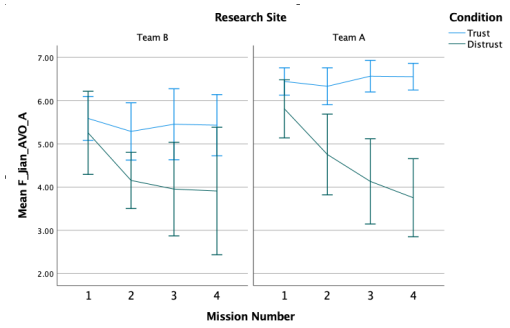

Fig. 3. **Trust in AVO-A as a system**, by Condition by Team by Mission (error bars represent standard error of the mean).

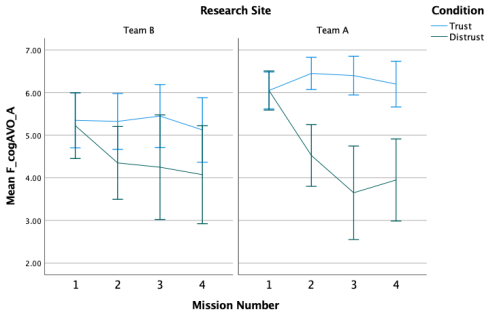

Fig. 4. **Cognition-based trust in AVO-A as a teammate**, by Condition by Team by Mission (error bars represent standard error of the mean)

For **Trust in Automated Systems Scale [65]**, there was a significant main effect of Condition (F [1, 37.21] = 19.95, p < .001). Participants in the Trust condition reported higher trust in AVO-A (M = 5.96, SE = .24) than those in the Distrust condition (M = 4.47, SE = .24). There was a trend towards a main effect of Team (research site) was found (F [1, 37.21] = 3.95, p = .05). Team A had higher trust in AVO-A (M = 5.54, SE = .24) than Team B did (M = 4.88, SE = .24). There was a significant main effect of Mission number (F [3, 69.76] = 7.28, p < .001). As missions proceeded, trust declined from Mission 1 (M = 5.78, SE = .20) drastically to Mission 2 (M = 5.13, SE = .20, p <.001). There was also a significant interaction effect between Condition and Mission number (F [3, 69.76] = 5.62, p = .002). It was only in Distrust condition did participants' trust in AVO-A decline significantly over missions. For Trust condition, trust did not decline significantly.

A 2 (Condition: Trust (T) vs. Distrust (D)) by 2 (Team/Research Site: Team A vs. Team B) ANOVA was conducted on **Affect-based Trust [87]**. There was no significant main effect of Condition (F [1, 36] = 3.20, p = .08). Nor was there a significant main effect of Team (F [1, 36] = .82, p = .37). However, there was a significant interaction effect between Condition and Team (F [1,36] = 4.41, p = .04). In Trust Condition, participants in Team A reported to have higher trust in AVO-A (M = 4.66, SE = .45) than participants in Team B (M = 3.30, SE = .45), whereas in Distrust Condition, participants in Team A reported to have lower trust in AVO-A (M = 2.90, SE = .45) than participants in Team B (M = 3.44, SE = .45).

4.1.2 Qualitative Insights from Team A (Manipulation HAT) participants.

In Trust condition, Team A participants' trust in AVO-A remained consistently high and was not very much affected by DEMPC-A's verbal trust spread. Eight out of 10 Team A participants in Trust condition reported that their trust in the AI teammate remained high

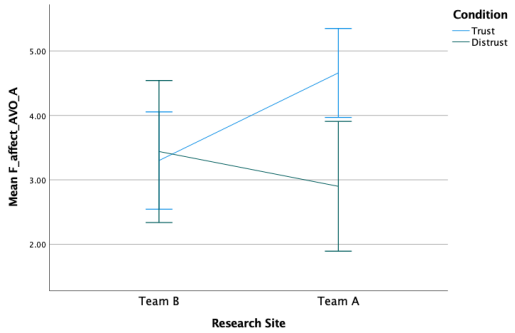

Fig. 5. **Affect-based trust in AVO-A**, by Condition by Team (error bars represent standard error of the mean).

and unchanged throughout the missions. Their trust was primarily driven by AVO-A's "prompt responses", "accurate information", and "immediate execution of requested actions", rather than DEMPC-A's comments. As the following quote suggest,

> "I was not much focused about comments on AVO-A. It (AVO-A) made me trust because giving the correct coordinates, not other people's comments." -13A (Trust, Male)

In Distrust condition, Team A participants' trust in AVO-A declined over the missions due to their observations of its objective performance, rather than being influenced by DEMPC-A's verbal spread of distrust. Participants' trust in AVO-A was heavily tied to perceived competence. When AVO-A failed to execute tasks accurately or efficiently, trust deteriorated, as these failures directly affected participants' ability to complete their tasks and had a cascading impact on the entire team.

> "When working with AVO-A, there was a slight competency issues with that, the AI was not able to adjust altitude and the airspeed at a particular moment, so there was miscommunication or less coordination in adjusting those features, it was delaying things. Eventually it affected the other team members. This build up the distrust as it is not working in a proper manner, and the team is getting affected because the PLO is completely dependent on the AVO. For AVO-A, what DEMPC say about it was not the problem. The problem was its competency" -3A (Distrust, Male)

When discussing their trust in AVO-A, Team A participants primarily referenced their direct experiences, such as how its misinformation or failure to adjust parameters undermined their own tasks. The impact of DEMPC-A's distrust spread appeared minimal, serving at most to reinforce or confirm existing distrust. For instance, Participant 9A viewed the distrust spread with skepticism, choosing to independently assess AVO-A's performance rather than immediately accepting the distrust.

> "(DEMPC's comments) made me put it on the radar. I don't trust the word of new people right away. I just thought, Okay, that's interesting. Let's watch what this AI does not just judge it for its actions." -9A (Distrust, Male)

4.1.3 ***Qualitative Insights from Team B (Collaborating HAT) participants.*** Consistent with the statistical results, Team B participants' trust in AVO-A was also stable across missions in Trust condition, while declined over the missions in response to the spread of distrust, though to a lesser extent and with greater individual variance compared to Team A participants (see Figures 3 and 4).

Their reflections revealed that nearly all participants (9/10) were unaffected by the **trust spread**. However, responses to the **distrust spread** were evenly split: half (5/10) reported that their trust in AVO-A was influenced by it, while the other half (5/10) stated it was not, attributing this to their lack of direct interaction with it.

Almost all (9/10) were not influenced by the trust spread due to lack of direct interaction with trusted AI teammate. Team B participants reported to have limited direct interaction with AVO-A and resisted being influenced by the word-of-mouth spread of trust. Many stated that without first-hand experience, they had no basis for adjusting their trust levels, resulting in a neutral and steady perception of AVO-A.

> "I never interacted with their AVO as far as I know. So I have no idea or basis for whether I trusted them more or less. Yeah, didn't change." -13B (Trust, Male)

Participant 10B noted that despite noticing DEMPC-A's trust spread about AVO-A, her trust in the AI teammate was intact.

> "I did notice the DEMPC(-A) did make comments every once in a while saying they(AVO-A)'re really contributing. I didn't really feel that that impacted how I was feeling about the AVO. The presence of the AVO wasn't super prominent there. -10B (Trust, Female)

5/10 remained unaffected by the distrust spread due to lack of direct interaction. Similar to those unaffected by the trust spread, five participants noted that without direct experience or communication, they had no basis for assessing AVO-A's reliability and their trust in them remained unaffected by DEMPC-A's comments.

> "(my trust in AVO-A) really stayed the same, because I don't think I had any personal interaction with them. There was nothing that they asked me to do, or I'd ask them to do. So, I can't say their (DEMPC-A's) words impacted me." -3B (Distrust, Female)

Participant 26B expressed a preference for forming his own judgments about AVO-A through direct observation, rather than relying on the input from others.

> "I would let the other teams' members show who they are, besides taking this person's input." -26B (Distrust, Male)

5/10 experienced a decline in trust toward AVO-A due to the distrust spread, despite lacking direct knowledge of AVO-A's actions. These people's trust erosion stemmed from repeated exposure to DEMPC-A's critical remarks, leading them to assume the concerns were valid. Despite not knowing what was going within Team A, Participant 12B stated that the spread of distrust caused him to reduce his trust in AVO-A.

> "I guess the only reason it (my trust in AVO-A) decreased was because what they (DEMPC-A) were saying but I don't have any knowledge of what was going on." -12B (Distrust, Male)

Some individuals' decreased trust in AVO-A stemmed from their own observations of their poor collective task performance, which they attributed to AVO-A, as informed by DEMPC-A's spread of distrust. For instance, Participant 9B said,

> "It (My trust in AVO-A) actually went down. Because we weren't able to complete session two, because they kept going the wrong way. And then I was told, DEMPC-A kept saying, because they didn't even trust him (AVO-A), so I didn't. If they didn't trust him, I wasn't going to trust him." -9B (Distrust, Male)

Similarly, Participant 15B articulated that he wouldn't have known it's the AVO-A's lack of skill that caused the other team to fall behind if their own member DEMPC-A had not told him so, and that he had no reason to not trust the distrust spreader's words.

> "(My trust in AVO-A) definitely got worse, because I would hear from the navigator on their team about how their AI pilot it's doing everything wrong, and that's why they can't take good pictures. I don't know if that's true. I'm gonna assume it is. Why they would lie about that. So over time, my trust decreased based on the performance of their pilot. Because I wouldn't have known about the lack of skill on the part of the pilot if the DEMPC didn't communicate that." -15B (Distrust, Male)

Participant 19B stated that DEMPC-A's spread of distrust of AVO-A made her lose trust in both of them.

> "I think my trust in them decreased throughout the missions, because the DEMPC(-A) was saying, Oh they're untrustworthy. I'd say my trust in both of them decreased."-19B (Distrust, Female)

4.2 Trust in DEMPC-A, the (Dis)Trust Spreader (RQ2)

4.2.1 ***Statistical Results.*** For **Cognition-based Trust**, there was no significant main effect of Condition (F [1, 37.08] = .50, p = .48). A significant main effect of Team (research site) was found (F [1, 37.08] = 9.54, p = .004). Participants in Team A reported higher trust in DEMPC-A (M = 6.15, SE = .22) than those in Team B (M = 5.21, SE = .22). There was no significant main effect of Mission number (F [3, 65.85] = .83, p = .48), nor were there any significant interaction effects (ps > .48).

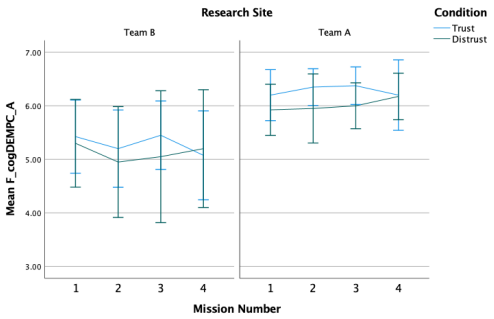

Fig. 6. **Cognition-based trust in DEMPC-A**, by Condition by Team by Mission (error bars represent standard error of the mean).

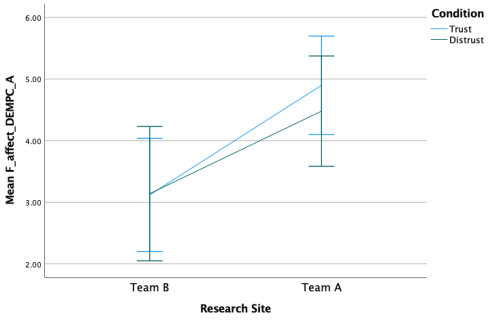

Fig. 7. **Affect-based trust in DEMPC-A**, by Condition by Team (error bars represent standard error of the mean)

For **Affect-based Trust**, there was no significant main effect of Condition (F [1, 36] = .18, p = .67). But there was a significant main effect of Team (F [1, 36] = 11.22, p = .002). Participants in Team A reported to have higher trust in DEMPC-A (M = 4.69, SE = .33) than participants in Team B (M = 3.13, SE = .33). There was no significant interaction effect between Condition and Team (F [1,36] = .22, p = .64).

4.2.2 ***Qualitative Insights from Team A (Manipulation HAT) participants.*** Regardless of the condition, Team A participants' trust in DEMPC-A was consistent and remained high throughout missions (see Figure 6). In line with this, our analysis of the interviews reveals that such strong consistent trust comes from the perception that DEMPC-A "consistently gave accurate data", "knew what they were doing", "prompt in response", "helped (me) a lot". In other words, **they trusted the**

teammate primarily based on their task performance and how they made the participant's job easier. As for their trust or distrust spreading behaviors, participants noted that they were not a major factor in shaping their trust in them.

> "[How did DEMPC's statements about AVO influence your trust or distrust in the DEMPC?] No, it did not. I would say neither. Not trust building, not distrust building. It can be motivating sometimes. But that's not why I trusted them." -14A (Trust, Female)

Team A participants in Distrust condition expressed a tension between trusting DEMPC-A for their strong task performance and distrusting them for their unprofessional and insensitive distrust spreading behavior. For instance, Participant 7A noted that while DEMPC-A's frequent complaints about AVO-A in an open forum were unnecessary and reduced his trust, he still found DEMPC-A's data accurate, which did not influence his trust in their performance.

> "He was complaining about the AI pilot a lot. I don't think it was needed, and then it was in an open form. So I thought that was a factor reduce the trust. But then I think the data DEMPC-A gave to me was pretty accurate, correct. So that (complaining) was not a factor, in terms of trust." -7A (Distrust, Male)

Ultimately, participants' evaluation remained largely task-focused, with competence and responsiveness outweighed interpersonal issues in shaping the trust. For instance, Participant 16A's trust in DEMPC-A was primarily driven by their responsiveness and reliability in task-related interactions. While she disliked the spreading behaviors, these concerns did not translate into distrust.

> "because every time I needed something from DEMPC and every time I asked, within a few seconds, he would respond back. So I think that is why I trust him very much. I just didn't like his other actions. But it's not distrust." -16A (Distrust, Female)

4.2.3 ***Qualitative Insights from Team B (Collaborating HAT) participants.*** In line with the statistical results, Team B participants' trust in DEMPC-A in both Trust and Distrust conditions showed greater variance than that of Team A participants (see Figure 6). Our qualitative analysis suggests that while some (2/10) found DEMPC-A's trust spread to be positive, others (3/10) expressed strong resentment. But half (5/10) reported to be not influenced by the trust spread.

The trust spread increased some (2/10) participants' trust in the spreader as it signals camaraderie and created lightheartedness. For instance, Participant 6B believed that DEMPC-A's compliments toward AVO-A increased his trust in DEMPC-A, as this verbal behavior made them seem more humorous and conveyed a sense of team spirit particularly desirable in this setting.

> "They kept complimenting the AVO. I thought it was funny. It definitely build more trust. It made it more lighthearted that helps build a sense of camaraderie or team spirit" -6B (Trust, Male)

Some (3/10) found the trust spread to be disingenuous and passive-aggressive, and therefore trusted the spreader less. For instance, Participant 22B expressed a strong negative reaction to and skepticism about DEMPC-A's trust spread, as the praise of their own team member came across as insincere or biased, making the participant's trust in the trust spreader drop significantly.

> "It (My trust in DEMPC-A) got lower. Definitely some very positive comments they made about their own member. Whatever the letters are, disingenuous. It rubbed me the wrong way... it shaded the whole experience, but mostly just the DEMPC." -22B (Trust, Male)

Participant 5B explicitly resented DEMPC-A, feeling that their praise of their own AI teammate, especially when she expressed difficulty completing her task, was dismissive and even passive-aggressive. This behavior made her feel inferior and undermined her trust in DEMPC-A.

> "They (DEMPC-A) were a jerk. What they were doing is, every time I had to, say that my photo is blurry, or I didn't get the photo, they would say, oh, that AVO on Team A is really good. Or, AVO is great rockin it. It was just kind of like, well, that doesn't make me feel really good about what I'm doing." -5B (Trust, Female)

One person explained how his trust in DEMPC-A was not influenced by the trust spreading behavior in terms of work; but in terms of social interactions, he would not trust them. This aligns with the quantitative result that Team B participants' affect-based trust in the DEMPC-A was significantly lower than that of Team A participants (see Figure 7).

> "(trust in DEMPC-A) was fine, minus the AVO highlights they kept giving. I just ignored it. I don't care. I mean, they did their job, and that's what I was looking for. Would I have a beer with them? Probably not. So I guess to distinguish the two, for work, it didn't change my trust, but social settings, yes." -26B (Trust, Male)

Most (5/10) were not influenced by the trust spread. Half of Team B participants in Trust condition reported that their trust in DEMPC-A remained constant and was not affected by their trust spreading behavior. Despite noticing the spread, participants felt detached from what was going on in the other team that was unrelated to their own task at hand.

> "That's nice that they're giving high fives over there, but it didn't matter to what I was doing or how I trusted them." -14B (T)

Most (6/10) expressed negative attitudes towards DEMPC-A after their distrust spread. Participants expressed a decline in trust toward DEMPC-A due to their public statements about AVO-A. They perceived this as unprofessional and damaging, causing them to question both DEMPC-A's judgment and AVO's reliability.

> "I had trust in the DEMPC at the beginning, and then once the DEMPC start saying all the stuff about the AVO, that's when it was a slip slope or steady decrease." -25B (Distrust, Female)

Participant 11B distinguished between trust in task performance and respect for DEMPC-A. He wasn't sure if he trusted DEMPC-A, since he had no way of knowing whether the other team completed the mission. However, he was certain he had lost respect for how they handled the situation.

> "that was pretty interesting because they started talking about AVO-A, but what I couldn't discern was if AVO-A was still getting to the locations. When you have a leadership that overtly shows discontent, that creates lack of trust, that's uncouth. Trust isn't maybe the right word. Did I trust that they knew what they're doing? That's the thing I don't know, I don't know if the mission was getting done on the other side. So strictly speaking, it's not a matter of trust, it's a matter of respect maybe? I lost respect for them. I didn't necessarily lose trust, because I don't know their mission was completed or not." 11B (Distrust, Male)

These responses illustrate a distinction between trust in task execution and trust in interpersonal dynamics. Participants expressed dissatisfaction with DEMPC-A's approach to handling relationships within their team, even though their trust in DEMPC-A's abilities to complete the mission remains uncertain.

Some (4/10) participants' trust in DEMPC-A was not influenced by the distrust spread. Participant 7B acknowledged the negative comments about AVO-A but chose to ignore them because she felt the criticism was irrelevant and unjustified, given the team's overall success.

> "It (My trust in DEMPC-A) didn't really change. I know they kept saying something about AVO, and I just ignored it because I thought it was dumb. It didn't make any sense, because everybody was being successful. If I was working with that team, I would be slightly annoyed, but I wouldn't have to lose trust, because we were still being successful. So it didn't impact the mission." -7B (Distrust, Female)

Despite DEMPC-A's distrust spread, four participants did not let such a behavior affect their trust in the spreader because they saw task success as a more significant factor.

4.3 Trust in Individual Teams and Team of Teams (RQ3)

4.3.1 ***Statistical Results.***

Trust in Team A. There was no significant main effect of Condition (F [1, 36.00] = 1.07, p = .31) or Team (F [1, 36.00] = .67, p = .42), or Mission (F [3, 76.91] = 2.22, p = .09). Nor were there any interaction effects (Fs [3, 76.91] < 1.91, ps > .18). Participants' trust in Team A as a whole did not differ significantly by Condition, by the Team they were in, or by Mission.

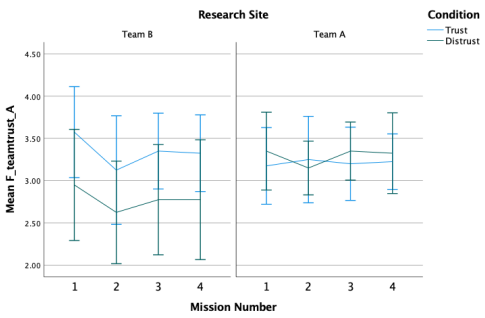

Fig. 8. **Trust in Team-A as a whole**, by Condition by Team by Mission (error bars represent standard error of the mean).

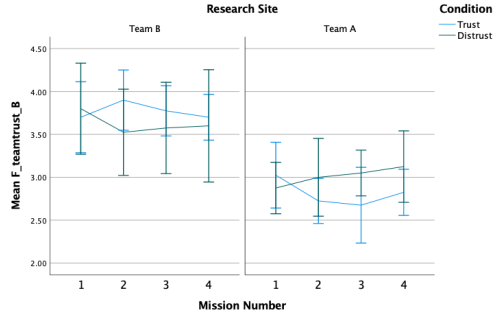

Fig. 9. **Trust in Team-B as a whole**, by Condition by Team by Mission (error bars represent standard error of the mean).

Trust in Team B. There was no significant main effect of Condition (F [1, 36.07] = .03, p = .87). There was a significant main effect of Team (F [1, 36.07] = 22.47, p < .001). Participants in Team B reported to have higher trust in Team-B as a whole (M = 3.70, SE = .12) than participants in Team A (M = 2.91, SE = .12). There was no significant main effect of Mission (F [3, 74.12] = .23, p = .87) or interaction effects (Fs [3, 74.12] < 2.04, ps > .12) found.

Perceived Team Trustworthiness of One's Own Team. In terms of how participants rated the trustworthiness of their own team, there was no significant main effect of Condition (F [1, 36] = .06, p = .81). There was a significant main effect of Team (F [1, 36] = 4.56, p = .04). Team B rated the trustworthiness of their own team as significantly higher (M = 4.11, SE = .13) than Team A rated theirs (M = 3.71, SE = .13). There was also a significant interaction effect between Condition and Team (F [1, 36] = 14.15, p < .001). In Trust Condition, Team A rated their own team's trustworthiness as significantly higher (M = 4.04, SE = .18) than Team B rated theirs (M = 3.74, SE = .18), whereas in Distrust Condition, Team A rated their own team's trustworthiness as significantly lower (M = 3.39, SE = .18) than Team B rated theirs (M = 4.48, SE = .18).

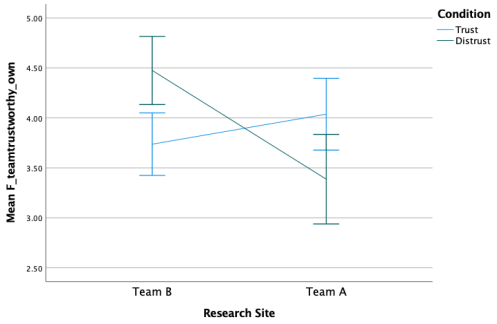

Fig. 10. **Perceived trustworthiness of one's own team**, by Condition by Team (error bars represent standard error of the mean).

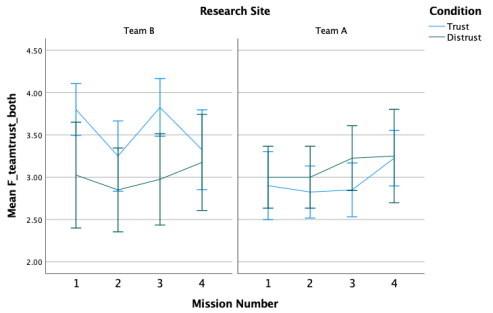

Fig. 11. **Trust in the ToT**, by Condition by Team by Mission (error bars represent standard error of the mean).

Multi-team-level Trust. For trust in the ToT, there was no significant main effect of Condition (F [1, 35.83] = 1.20, p = .28) or Team (F [1, 35.83] = 2.03, p = .16) or Mission (F [3, 73.45] = 2.35, p = .08). However, there was a significant interaction effect between Condition and Team (F [1, 35.83] = 4.33, p = .05). In Trust Condition, Team B trusted the entire ToT more (M = 3.55, SE = .17) than Team A (M = 2.95, SE = .17), whereas in Distrust Condition, Team A (M = 3.12, SE = .17) and Team B (M = 3.01, SE = .17)'s trust placed in the ToT was not much different.

4.3.2 *Qualitative Insights from Team A (Manipulation HAT) participants.*

Self-team evaluation: DEMPC-A's distrust spread and AVO-A's mistakes did not affect their trust in the entire team overall, as they were able to cope with the obstacles as a team. Despite experiencing trust declines in the AI teammate, some Team A participants maintained or even increased their trust in the team as a whole. This was largely due to their ability to adapt, collaborate effectively, and successfully complete the mission. Participant 3A emphasized that strong coordination between PLO and DEMPC compensated for AVO-A's shortcomings, leading to overall trust growth.

> "Trust in the entire team was completely increasing. [even though your trust in AVO-A decreased?] Yes, because as PLO and DEMPC we managed in a better way." -3A (Distrust, Male)

Similarly, Participant 7A acknowledged individual trust fluctuations but argued that team trust should not be measured as an average, instead valuing the team's collective ability to function despite conflicts.

> "[Even though your trust in individual teammates went down, your final trust in Team A was still six. Why is that?] Because at the end, we still managed to do things properly, even if there's conflicts, the mission was pretty good. I don't think you could measure a team's trust on an average, because maybe someone is trustworthy and someone isn't, but it's better if you are in a team. It's better to hold things together." -7A (Distrust, Male)

Participant 16A took a pragmatic approach, recognizing AVO-A's mistakes but adjusting accordingly, which ultimately reinforced their trust in the team's overall capability.

> "I think AVO made mistakes. But by then I already knew how to correct those mistakes, I would just check the speed or altitude and ask them to change. So I think in the overall team, my trust went up." -16A (Distrust, Female)

Cross-team evaluation. Team A participants' trust in Team B as a whole was primarily based on their interaction with and evaluation of their PLO counterpart (the other participant on Team B), because none of the participants interacted with other members on Team B. Participant 3A noted that since only the PLOs directly communicated across teams, trust was primarily built between individuals in that role rather than extending to the entire teams.

> "I don't think that there is a direct relationship between these two teams, because only PLO was communicating with the other PLO, so it was more like trust between PLOs instead of two teams." -3A (Distrust, Male)

Therefore, Team A participants' trust in their collaborating team as a whole was contingent upon their direct collaborator PLO-B's performance and communication effectiveness. As the following quote suggests, when delays occurred, such as waiting for Team B to complete their tasks or receiving slow responses, participants questioned Team B's efficiency and, in turn, reduced their trust in the team.

> "There was a time where they were lagging behind. It was like we are done with our first part of doing our own photos, and starting with the team photos. We completed our first experiment promptly, very quickly. We had to wait for Team B to get done with this. And it was quite a while, I was just sitting and was like, when is this guy's moving ahead with the second part of the experiment. So I would question on the efficiency, and the trust as team as a whole." -11A (Distrust, Male)

*4.3.3 **Qualitative Insights from Team B (Collaborating HAT) participants.***

Self-evaluation: Team B participants consistently trusted their own team. Although Team B participants rated their own team's trustworthiness significantly higher in Distrust than in Trust condition (Figure 10), their qualitative reflections revealed no notable differences across conditions. In both conditions, participants generally reported stable or increasing trust in their own team over time, primarily driven by task success, reliability, and effective communication.

> "My personal team seemed to increase the level of trust throughout the missions. Because we were able to build rapport. And there was a history of accurate information, and good communication." -8B (Trust, Male)

Cross-team evaluation: Several (2/10 from Trust, 3/10 from Distrust conditions) Team B participants' trust for Team A as a whole decreased as a result of the (dis)trust spread. This decline stemmed from skepticism toward DEMPC-A's intentions and the perception of a lack of team cohesion. Participant 5B questioned the motivations behind DEMPC-A's excessive praise of AVO-A, leading to distrust toward that individual and some doubt about Team A as a whole.

> "Trust just changed because of DEMPC on the team. The others really didn't (change). But DEMPC that was praising their AI pilot, not trust him like what are his motivations for doing that." -5B (Trust, Female)

In Distrust condition, Participant 19B felt that DEMPC-A's negative remarks about their AVO made Team A seem disconnected and lacking unity, which contributed to an overall decline in trust in the entire team.

> "I think my trust decreased as a whole for them, mainly due to communication and how the DEMPC was, saying bad things about their AVO, so it didn't seem like a unified team." -19B (Distrust, Female)

Participant 15B noted that he already did not trust his PLO counterpart, and the distrust spread about the AVO-A exacerbated his distrust in the team.

> "(My trust in Team A) went way down, mostly because the PLO on the other team that I just couldn't comprehend how he wasn't doing his job. And then what I was hearing about their AVO as well, that didn't help. So overall went down." -15B (Distrust, Male)

These responses show that trust in an entire team can be undermined by the actions of a single member, particularly when their behavior appears divisive (the spread of trust about AVO-A was perceived as divisive of the two teams, and the spread of distrust was perceived as divisive of one team). As such, loss of trust in one member of the other team can cascade into a broader distrust of the entire team.

Cross-team evaluation: Most (7/10 from Distrust, 7/10 from Trust conditions) of Team B participants' trust in Team A remained intact by the spread given the perceived mission success. Regardless of whether they were in Trust or Distrust condition, these participants maintained a steady level of trust in Team A as a whole, despite individual concerns about specific team members. Their trust judgments were primarily task-based, focusing on whether Team A responded to them promptly and successfully completed their objectives.

> "(Trust in Team A) was pretty much the same. They were responding to chat and trying to do what their job was. It stayed pretty constant. They all got their pictures taken and that was the objective. -12B (Distrust, Male)

4.4 Trust in Other Unmanipulated Teammates (AVO-B, DEMPC-B, PLO (participants' role))

Beyond our focal analyses, we also examined trust in unmanipulated teammates (AVO-B, DEMPC-B, and participants' own role, PLO). These analyses were conducted to ensure transparency and to test whether (dis)trust contagion might extend more broadly across all teammates. Consistent with our research questions, which centered on the manipulated AI teammate (AVO-A), the human trust/distrust spreader, and team-level constructs, these unmanipulated teammates were not hypothesized as primary sites of contagion. The absence of significant effects suggests that trust and distrust cues did not automatically generalize to all other teammates. Instead, contagion appeared targeted, shaping perceptions of the focal AI teammate and spreader, while leaving evaluations of other teammates relatively stable. This distinction suggests that (dis)trust contagion in multi-HAT contexts is not a diffuse process but one that follows specific social and task-relevant pathways.

5 Discussion

In this study, we set out to examine whether and how trustful and distrustful expressions toward an AI teammate can spread from one HAT to a collaborating HAT **(RQ0)**. Findings show that distrust is much easier than trust to spread. However, the mechanisms driving distrust contagion differ between intra-team and inter-team dynamics. Additionally, when encountering trust-damaging incidents, interconnected HATs exhibited in-group favoritism and out-group bias by distrusting both the individual responsible and that individual's entire team. In this section, we revisit the research questions to interpret these findings in relation to existing theory and literature, discuss their implications for designing effective interconnected HATs, and propose directions for future research.

5.1 Unpacking (Dis)Trust Spread across Individual, Team, and HAT Boundaries

5.1.1 ***Distrust spreads faster than trust. Intra-team trust toward AI forms through direct experience, while inter-team trust falls to word-of-mouth.*** While previous work has suggested that an AI's good reputation can influence user's initial trust [51] and that trust can be contagious within a HAT [35], our findings do not fully support this. In our study, trustful expressions did

not increase trust in the AI, whether within a team or between teams **(RQ1)**. This may be due to individuals' tendency to initially place a high level of trust in AI [36], a phenomenon known as the perfect automation schema [77]. As a result, there is little room for trust to increase. Thus, while our findings may suggest that trust is less easily spread than distrust, it would be premature to conclude this definitively. To verify this, future research should design experiments that prime participants to have lower initial trust in the AI teammate, allowing room for trust to grow and diffuse.

Our study further suggests that distrustful expressions about an AI teammate can spread from one team to a collaborating team, leading its participants to gradually lose trust in the distrusted AI teammate over missions, though to a lesser extent than those on the manipulation team **(RQ1)**. The interviews reveal that intra-team trust declined not solely due to word-of-mouth distrust but also because of participants' direct experiences with the AI teammate and their observations of its performance and competence. In contrast, inter-team trust in the AI was more influenced by word-of-mouth, as collaborating team participants often lack direct experience or knowledge about the AI. However, individual differences play a role in this susceptibility. These findings are reassuring in that individuals do not blindly trust an AI but instead calibrate their trust [115] based on direct observations of its performance, particularly when task interdependence is high (i.e., the participant's success is highly dependent on that of the AI). However, they are also concerning because direct interaction with or knowledge about an AI teammate may not always be available in ad-hoc or remotely collaborating HATs. In the absence of direct experience, people tend to rely on whatever social information is available [102], making them more susceptible to mistrusting the AI (i.e., either by trusting it when it is untrustworthy or distrusting it when it is reliable).

5.1.2 ***Trust in the (dis)trust spreader: in-group favoritism and out-group bias.*** Participants' trust in the spreader teammate does not appear to be significantly influenced by their verbal expressions of either trust or distrust toward the AI teammate. However, a general out-group bias or in-group favoritism is evident, as participants from the remote collaborating team trusted the spreader significantly less than those from the local team, regardless of the condition **(RQ2)**. This aligns with previous findings that trust toward out-group members requires more cognitive control and is generally lower compared to in-group trust [62].

The interviews revealed that local team participants based their trust in the spreader on their consistent performance and the extent to which they contributed to task completion. In contrast, participants from the remote collaborating team lacked direct task interaction with the spreader, making it harder to assess their trustworthiness. Additionally, some Team B participants perceived the spreader's trustful statements about the AI on Team A, when made at an inopportune moment, as passive-aggressive, implying a critique of their own competence. It remains unclear whether this perception stemmed from the spreader's out-group status or if it heightened participants' awareness of their own out-group status. But the fact that such perceptions were absent among Team A participants suggests that team boundaries shape how statements about an AI teammate are interpreted, with in-group members being more likely to give the spreader the benefit of the doubt, whereas out-group members may be more prone to misinterpret the spreader's behavior, which can lead to reduced trust, negative evaluations, and strained relations [25].

5.1.3 ***Team-level trust dynamics within and across HATs.*** For team-level trust **(RQ3)**, the dynamics differ between intra-team and inter-team contexts. Intra-HAT trust does not simply emerge from trust in individual teammates but rather depends on how well team members collaborate to achieve shared goals and collectively overcome challenges. In contrast, inter-HAT trust is shaped by individuals' direct interactions with specific members of the collaborating team. As a result, trust in those individuals tends to extend to the entire team (see Section **??**). This difference

highlights the importance of direct interaction, communication, and collective problem-solving in assessing and calibrating trust, especially when navigating obstacles and risks. Trust research has long recognized risk as a fundamental factor in assessing a teammate's trustworthiness [84]. Risk creates uncertainty, requiring individuals to make judgments about whether to depend on others in situations where outcomes are unpredictable [107]. Our findings extend this understanding by demonstrating that team-level trust goes beyond trust in individual members and is shaped by the collective ability of a team to navigate challenges. This overall team-level trust can in turn enhance trust in individual teammates through various cognitive and social processes [35, 55].

Another interesting finding regarding team-level trust is that Team B participants rated their own team's trustworthiness significantly higher in the Distrust condition than in the Trust condition. This contrasts with the more intuitive finding that Team A participants rated their own team's trustworthiness higher in the Trust condition and lower in the Distrust condition (see Figure 10). We suspect that social comparison [39] may have occurred at the team level among these HATs. Social comparison theory posits that individuals evaluate their own abilities and worth by comparing themselves to others. This process can occur through upward comparisons (with those perceived as better off) or downward comparisons (with those perceived as worse off). Downward social comparisons often serve to enhance self-esteem and self-worth by highlighting one's relative advantage over others (e.g., [73, 78]). When Team B participants observed Team A members expressing distrust toward their own AI teammate, they may have engaged in downward social comparison, perceiving Team A as less cohesive and lacking team spirit. This perception could lead Team B members to view their own team more favorably, thereby boosting their collective self-esteem and reinforcing intra-team trust. Recent work supports the notion that social comparison can happen at the team and organizational levels [83] as well as between humans and AI agents in team settings [34].

5.2 Theoretical Implications

The findings of this study offer theoretical insights into trust contagion within and across HATs. Drawing on our results, as well as emotional contagion theory [3, 54] and the integrative model of trust [84], we discuss theoretical implications for understanding how trust and distrust contagion may occur in interconnected HAT contexts.

First, our findings suggest that distrust spreads more readily than trust, both within and across HATs, which aligns with emotional contagion work [3], which indicates that negativity travels faster and evokes stronger emotional, behavioral, and cognitive responses compared to positivity [10, 101]. Indeed, research has shown that people tend to pay more attention to and give greater weight to negative information [22, 52].For instance, Bartel and Saavedra [4] found that work groups were more likely to converge toward unpleasant moods than toward pleasant ones. Extending this literature, our results highlight an additional factor unique to the HAT context: individuals' predisposition to place greater trust in AI [92]) may further limit the spread of trust relative to distrust contagion.

Second, our findings highlight potential cognitive processes underlying trust and distrust contagion **within** a HAT, which differ from those driving contagion **across** HATs. This distinction arises primarily from the availability of firsthand information and direct interaction with the AI teammate in question. Similar to emotional contagion, trust and distrust contagion require attentional processes, where individuals must first notice and process (dis)trustful remarks. However, unlike emotional contagion, which can occur subconsciously and automatically [38], trust and distrust contagion involve deliberate **analytical thinking** [9, 44]. That is, individuals verify the AI teammate's trustworthiness against the (dis)trust spread by directly observing its reliability and performance. The outcome of this verification process determines whether (dis)trust spreads to the

individual. Additionally, through these analytical processes, individuals develop coping strategies to manage a distrusted AI and navigate challenges as a team. Consequently, distrust contagion does not necessarily escalate to the team level or impair team performance. Instead, it can enhance team resilience [53], as members work together to overcome obstacles posed by the distrusted AI teammate.

Third, our findings reveal more complex processes underlying trust and distrust contagion **across** HATs. Lacking direct knowledge and interaction with the AI in the other HAT, individuals on the remote HAT are unable to engage in deliberate analytical processes to effectively assess the AI teammate's reliability and performance, even if they wish to do so. Instead, they are relegated to relying on external social information [102] to build trust or distrust toward the AI on the other team, though the extent of this reliance may vary based on individual differences, such as propensity to trust and cognitive style. Our findings also indicate that individuals draw on other cognitive and social processes to assess the situation and their trust toward their own team, the other team, and individual members. Specifically, intergroup bias [25] emerges and is amplified not only by distrust contagion but also by trust contagion. For instance, praise for an in-group AI teammate may be perceived negatively by the out-group. Additionally, social comparison [39] may arise as a consequence of distrust contagion across HATs, leading the remote HAT to perceive itself as better off than the HAT experiencing internal trust issues.

These theoretical insights offer a foundation for future research to systematically explore the underlying processes of trust and distrust contagion within and across HATs. For example, future research could verify whether analytical processes truly underlie (dis)trust contagion by manipulating cognitive load and time pressure, to observe whether those in analytical processing conditions exhibit more deliberate, consistent trust judgments and behaviors, as analytical thinking is more effortful and less likely to engage under time pressure [38]. By tracking how trust in AI spreads within and across HATs, researchers could determine if analytical processing leads to more durable, rational trust contagion, compared to trust spreading via heuristics in low-effort conditions.

5.3 Designing Interconnected HATs with Thoughtful Trust Calibration

5.3.1 ***Enhancing AI transparency and situational awareness across interconnected HATs to effectively mitigate distrust contagion.*** First, the lack of direct interaction with the local AI teammate and limited awareness of the local team's activities make remote HAT members particularly vulnerable to misinformation and misunderstandings. Without direct visibility into the AI teammate's actual performance and behavior, remote collaborators are more likely to rely on indirect information, which may be biased or misleading, thereby increasing the likelihood of distrust spreading across teams. This vulnerability underscores the critical need to enhance AI transparency and situational awareness across interconnected HATs to effectively mitigate distrust contagion. Specifically, AI's actions, decision-making processes, and performance metrics should be clearly communicated not only to immediate local teammates but also shared with remote collaborators. Enhanced transparency may include providing regular performance summaries, real-time updates on AI tasks and goals, proactive alerts regarding potential performance issues or failures, and information about any corrective actions taken by the AI. Additionally, improving situational awareness requires mechanisms and cross-team information sharing interface for remote team members to obtain accurate, timely information about local team dynamics and AI reliability.By adopting cross-HAT transparency measures, the Team of Teams can ensure all members maintain informed perceptions, thereby preserving trust and collaboration across distributed HAT environments.

However, transparency features may need to be simplified for remote collaborators who may have limited cognitive resources to spare due to their focus on their own team's activities. One practical solution is to leverage intuitive, real-time color-coded signals: green indicating the AI is performing

as expected, red signaling performance issues requiring attention, and yellow representing instances where the AI has encountered but successfully corrected an error. An additional indicator could be used to provide remote team members with general situational awareness of overall team coordination and activity.

These findings also point to the role of transparency in **managing (dis)trust spreaders**. Because spreaders inevitably act as early interpreters of team behavior or AI performance, providing clearer contextual and system-state information can reduce over-reliance on their second-hand cues. Transparency can help teammates distinguish between justified warnings and subjective impressions, thereby preventing unintentional distrust cascades in settings where spreaders are necessary or unavoidable.

5.3.2 ***Leveraging external information to calibrate trust in AI.*** Second, remote HAT members' susceptibility to external influence presents an opportunity to calibrate their trust in AI, thereby reducing over-reliance on AI and complacency [95]. Given humans' natural tendency to place excessive trust in AI [92]), providing external information or subtle warnings about an AI teammate, whom they do not interact with directly, can help counteract blind trust. For instance, providing explicit yet unobtrusive alerts about AI's occasional performance deviations can prompt remote collaborators to adopt a more critical approach. Additionally, incorporating periodic reminders emphasizing areas requiring human judgment can further encourage thoughtful engagement and proactive monitoring of AI-driven outputs. By strategically leveraging external information, organizations can promote balanced reliance on AI, ensuring team members remain actively involved in collaborative processes and prepared to intervene when necessary.

5.3.3 ***Personalization of trust calibration strategies.*** Third, our findings suggest that trust calibration techniques should account for individual differences in susceptibility to word-of-mouth distrust spread. Although our sample size did not permit modeling these differences quantitatively, participants' narratives indicate that susceptibility may be shaped by factors such as prior experiences with AI, baseline attitudes toward automation, risk sensitivity, and comfort with uncertainty. Future work with larger and more diverse samples is needed to examine how these individual differences shape the degree to which people accept, resist, or reinterpret second-hand distrust cues. To effectively address these differences, each HAT member should maintain a profile documenting their past experiences collaborating with AI, attitudes toward technology, propensity to trust others, and cognitive style (e.g., analytical vs. intuitive). Such profiles would serve as comprehensive indices to determine and implement the most appropriate and effective trust calibration strategies on an individual basis. Tailored interventions, such as targeted training sessions [70], personalized reminders, or adaptive feedback mechanisms [56], could be developed based on these profiles. By customizing trust calibration approaches according to individual differences, organizations can significantly reduce the risks associated with both over-reliance on AI and undue skepticism, ultimately fostering a balanced, informed, and effective collaboration across HATs.

These design insights, grounded in our study's findings, are valuable across various CSCW domains, particularly as interconnected HATs become integral to fields like medical healthcare and emergency response. In healthcare, AI systems support diagnostics [11], treatment recommendations [48], and robotic surgery across multiple medical teams [96]. Enhanced AI transparency through clear and timely communication, and simplified and intuitive performance indicators could help medical professionals maintain appropriate trust and swiftly respond to AI recommendations, ultimately improving patient care outcomes. Similarly, AI-powered coordination tools assist emergency response teams [6, 124] who often operate across different locations and need to rely on second-hand information about the collaborating team's AI capabilities. Calibrating trust through external cues or subtle warnings about the reliability and potential limitations of AI capabilities

can reduce complacency, prompting responders to remain vigilant and engaged. Personalized trust calibration strategies based on individual profiles can further optimize coordination, ensuring team members leverage AI support effectively while staying prepared to act decisively during critical moments. By applying these tailored strategies, entities in healthcare and emergency response settings can significantly enhance the effectiveness, responsiveness, and resilience of their interconnected HATs.

5.4 Limitations and Future Work

The findings reported in this paper should be interpreted with several limitations. First, to simulate a realistic human-AI teaming task commonly found in real-world HAT application domains such as emergency response, we utilized a collaborative reconnaissance task with UAVs and conducted the study on the CERTT research platform. While this setup provides a realistic experience and reflects the coordination, task interdependence, situational complexity, and uncertainty typical of human-AI teaming applications, it also imposes constraints on participants' actions, behaviors, and communication. As a result, our findings may primarily apply to high-stakes, task-specific HAT contexts. Future research is needed to explore whether these findings can be generalized to other HAT applications with lower time sensitivity and reduced task interdependence between humans and AI. Second, we employed the Wizard of Oz method to maintain experimental control and consistency. As such, the AI teammate consistently made the same mistake (i.e., providing the wrong altitude) until participants told it to correct. Over time, participants adapted and learned to manage this predictable error. However, real-world AI teammates, especially contemporary conversational LLM-based systems, may generate more adaptive, contextualized, or variable behaviors. This places limits on external validity, as trust contagion dynamics may differ when working with more capable AI systems whose cues are less predictable or more richly expressed. Future research should examine how trust recalibrates when AI performance changes unpredictably or when the AI proactively communicates its reasoning or uncertainty. Third, we acknowledge that the sample size of this study is relatively small and that demographic imbalances exist across teams and conditions, including age differences. While we detected statistically significant results, unmodeled individual differences may introduce additional variability. Larger and more demographically balanced samples would support finer-grained modeling of how individual differences influence (dis)trust contagion. Fourth, our design relied on a text-based cross-team communication channel, which served as the only way for Team B to receive the spreader's trust cues. Participants could not directly observe the other team's task performance; instead, they inferred performance only from the final photograph (clear vs. blurred). As a result, social information ("word-of-mouth" via chat) and outcome-based cues (photo quality) were naturally intertwined in how trust signals traveled between teams. Future work could vary or restrict the chat channel or decouple it from outcome visibility (e.g., hiding the photo or limiting cross-team remarks) to distinguish how much trust contagion is driven by social information versus inferred task success. These boundaries help clarify how the observed mechanisms may evolve as AI capabilities and team communication structures change. Additionally, although RPAS missions are high-stakes in real-world settings, participants in our study did not face real consequences or incentives, and their sense of task importance stemmed from the coordination demands rather than actual risk. This may attenuate or shift certain trust dynamics, and future work should examine whether stronger contextual cues or consequential incentives more faithfully elicit high-stakes perceptions. Lastly, both teams in our study performed similar tasks and possessed a relatively clear understanding of each other's roles and responsibilities. This symmetry may reduce uncertainty compared to real-world multiteam arrangements, where teams often carry out interdependent but distinct tasks with limited insight into one another's processes. Such asymmetry may heighten ambiguity and increase reliance on second-hand information, potentially amplifying

trust or distrust contagion. Future work should examine how these dynamics unfold when teams differ more substantially in expertise, task structure, or situational awareness.

6 Conclusion

In this paper, we present an experiment involving two interconnected HATs (N=40) across the U.S., with each team consisting of two human members and one AI working together on a simulated reconnaissance mission, to examine how a human teammate's trustful and distrustful expressions toward an AI on their team spread within and across HATs. Our findings demonstrate that distrust toward the AI spreads more easily than trust, both within individual teams and across interconnected HATs. While intra-team (dis)trust is shaped by direct interaction, inter-team (dis)trust is more susceptible to the influence of word-of-mouth. Furthermore, participants' trust in the spreader of (dis)trust, along with their overall team-level trust, reflected tendencies of in-group favoritism and out-group bias.

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