

Trust Contagion and Transfer in Multi-Human Multi-Unmanned Aerial Vehicle (UAV) Teams

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Abstract

Trust in human-autonomy teams remains understudied beyond dyads. This study examined trust contagion between teammates and trust transfer between UAVs in two-human, two-UAV teams. Fifty-three human dyads, one Commander and one Intelligence Support operator, completed a target acquisition task in a 3 (UAV reliability: High-High, Mixed, Low-Low; within-subjects) $\times$ 2 (primed trust: Trust, Distrust; between-subjects) design. Intelligence Supports were primed with a 100% or 57% UAV reliability video, which shifted their initial trust. These attitudes, however, did not spread to the Commander. Instead, the higher-authority Commander pulled distrust-primed Intelligence Support's trust upward during pre-task discussion. Once the task began, UAV reliability overrode the social effects. Trust transferred positively between systems: the reliable UAV elevated trust in the less reliable UAV, contrary to prior findings of negative transfer, likely due to differences in task characteristics. Role hierarchy and task characteristics thus emerge as key moderators of trust in multi-human multi-agent teams.

Keywords

trust in autonomy, interpersonal influence, trust transfer, power dynamics, task characteristics

Introduction

As AI systems evolve from tools to autonomous teammates, trust has become central to effective human-autonomy team (HAT) cooperation (Chiou & Lee, 2021; Guo et al., 2023). Most HAT research focuses on dyadic relationships, yet non-dyadic teams are increasingly prevalent (Fraune et al., 2015). These complex hybrid teams introduce dynamics that dyadic models cannot capture. Individuals possess diverse dispositional trust in AI teammates (Schneiders et al., 2022). Additionally, cognitive properties of a group differ significantly from those who comprise it due to division of cognitive labor or group-formed consensus (Hutchins, 1996). The present study addresses this gap by examining two trust propagation mechanisms in a co-located multi-human multi-UAV team: *trust contagion*, through which trust attitudes spread between human teammates, and *trust transfer*, through which trust in one UAV shapes trust in another UAV.

Background

Trust, defined as “the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability” (Lee & See, 2004), is foundational

to effective HAT (Parasuraman & Riley, 1997). When moving beyond dyadic HATs, trust operates at multiple levels: between individual members (human and AI) and across dyads within the team (human-human; human-AI). Huang et al.'s (2021) distributed dynamic team trust (D2T2) framework proposes that team trust is dynamic and transitive, influenced through conversations and training. Building on this, we investigate *trust contagion*, where one person's trust or distrust towards a teammate can generate similar affective responses in others through social interactions (Duan et al., 2025; Rojas et al., 2025). Prior studies have relied on confederates with scripted interactions, limiting ecological validity. We instead employed trust priming during training, leveraging evidence that introductory information about automation reliability shapes initial trust (Hoff & Bashir, 2015; Körber et al., 2018; Lee & See, 2004). We hypothesized that (H1) training materials effectively prime initial trust in

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AI-controlled UAVs and (H2) this primed trust is contagious through social interactions.

A second trust mechanism is *trust transfer* between systems. System-Wide Trust (SWT) theory proposes that trust generalizes across related autonomous systems, while Component-Specific Trust (CST) suggests users maintain distinct evaluations based on each system's individual performance (Keller & Rice, 2009). Early evidence largely supported SWT, showing negative trust transfer from inaccurate systems to otherwise reliable ones (Geels-Blair et al., 2013; Walliser et al., 2016). More recent work suggests CST may dominate when operators have high task familiarity and decisional freedom (Lopez & Pak, 2020; Lyons et al., 2024). Whether SWT or CST prevails in multi-human multi-AI teams remains underexplored. We hypothesized (H3) that when two UAVs differ in reliability, the less reliable system will reduce trust in the co-present more reliable system.

Approach

This study employed a 3 (UAV reliability: High-High, Mixed, Low-Low; within-subjects) $\times$ 2 (primed trust: Trust, Distrust; between-subjects) mixed design. Fifty-three dyads ($N=106$; 37% female; ages 18–64, $M=19.73$, $SD=4.73$) comprised two human operators—Commander (CO) and Intelligence Support (IS)—and two AI-powered UAVs (North, South) performing a Reconnaissance, Surveillance, and Target Acquisition (RSTA) task. UAV reliability was manipulated at high (~95%) or low (~60%) accuracy, consistent with established thresholds (Chavaillaz et al., 2016), and counterbalanced via Latin square; in Mixed conditions, North maintained high reliability while South operated at low reliability.

After initial training in separate rooms, both participants provided baseline UAV trust ratings on a 7-point scale. IS then received a 30-second video showing UAV performance at either 100% accuracy (Trust condition) or 57% accuracy (Distrust condition) and re-rated their trust as a manipulation check. The priming video was intentionally brief to keep both operators' training durations roughly equal.

During the RSTA task, UAVs autonomously identified targets across three 8-minute videos; operators needed to monitor UAV performance and communicated freely with their teammates to evaluate each UAV's performance. Before each block, participants discussed expected UAV performance, with IS instructed to share first. Before the first block, they additionally provided independent trust ratings on a 7-point scale. After each block, both operators completed the Multi-Dimensional Measure of Trust (MDMT) (Ullman & Malle, 2019) for each UAV. The full session lasted 90 minutes. Data were analyzed using linear mixed models (LMM) in R (*lme4*, *emmeans*), with participant ID as a random effect, and Bonferroni-corrected pairwise comparisons for post-hoc tests.

Outcome

Manipulation Check

IS trust ratings showed a significant *Condition* $\times$ *Timepoint* interaction, $\beta=-2.27$, $t(51)=-6.85$, $p<.001$, $\omega^2=0.46$. Ratings increased in the Trust condition (pre-priming: $M=4.87$, $SE=0.21$; post-priming: $M=5.95$, $SE=0.21$; $p_{\text{adj}}<.001$, $d=-1.25$) and decreased in the Distrust condition (pre-priming: $M=4.71$, $SE=0.21$; post-priming: $M=3.52$, $SE=0.21$; $p_{\text{adj}}<.001$, $d=1.36$). Conditions diverged significantly post-priming ($p_{\text{adj}}<.001$, $d=1.70$), confirming H1 (see Figure 1).

Initial Exposure

To examine contagion before CO had any direct UAV performance exposure, we analyzed 7-point trust ratings before the first mission with *Role*, *Condition*, and *Timepoint* as predictors. The model revealed a significant three-way *Role* $\times$ *Condition* $\times$ *Timepoint* interaction ($\beta=0.94$, $t(102)=2.38$, $p=.02$, $\omega^2=0.04$), a significant *Role* $\times$ *Condition* interaction ($\beta=-1.50$, $t(151.73)=-3.43$, $p<.001$, $\omega^2=0.05$), and a main effect of *Condition* ($\beta=-0.82$, $t(151.73)=-2.64$, $p=.01$, $\omega^2=0.28$). Post hoc comparisons of the three-way interaction revealed that in the Distrust condition, trust increased post-discussion for both CO (pre: $M=4.96$, $SE=0.22$; post: $M=5.46$, $SE=0.22$; $p_{\text{adj}}=.01$, $d=-0.49$) and IS (pre: $M=3.58$, $SE=0.22$; post: $M=4.54$, $SE=0.22$; $p_{\text{adj}}<.001$, $d=-0.95$), while both remained stable in the Trust condition ($p_{\text{adj}}>.05$) (see Figure 2). This suggests CO pulled up IS's trust in Distrust condition. H2 was not supported.

Trust in UAVs

Post-task MDMT ratings were analyzed with *Condition*, *Reliability*, *UAV*, and *Role* as predictors.

Trust Contagion. No significant *Condition* effect or *Condition* $\times$ *Reliability* interaction emerged ($p>.05$). Instead, a strong *Reliability* main effect dominated ($p<.001$, $\omega^2=0.61$): High-High ($M=5.39$, $SE=0.11$) exceeded Mixed ($M=4.50$, $SE=0.11$), $p_{\text{adj}}<.001$, $d=0.87$, and Low-Low ($M=2.90$, $SE=0.11$), $p_{\text{adj}}<.001$, $d=2.46$. UAV reliability, not primed trust, drove post-task trust (see Figure 3). H2 was not supported.

Trust Transfer. A significant *Reliability* $\times$ *UAV* interaction emerged ($\beta=-2.43$, $t(520)=-9.80$, $p<.001$, $\omega^2=0.25$). For North, trust did not differ between High-High and Mixed ($p_{\text{adj}}>.05$). For South, High-High ($M=5.53$) exceeded Mixed ($M=3.50$; $p_{\text{adj}}<.001$, $d=1.41$) and Low-Low ($M=2.77$; $p_{\text{adj}}<.001$). Critically, South's trust in Mixed was significantly higher than in Low-Low despite lower actual performance (58% vs. 63%; $p_{\text{adj}}<.001$, $d=0.51$), indicating positive SWT where the reliable North elevated trust in the less accurate

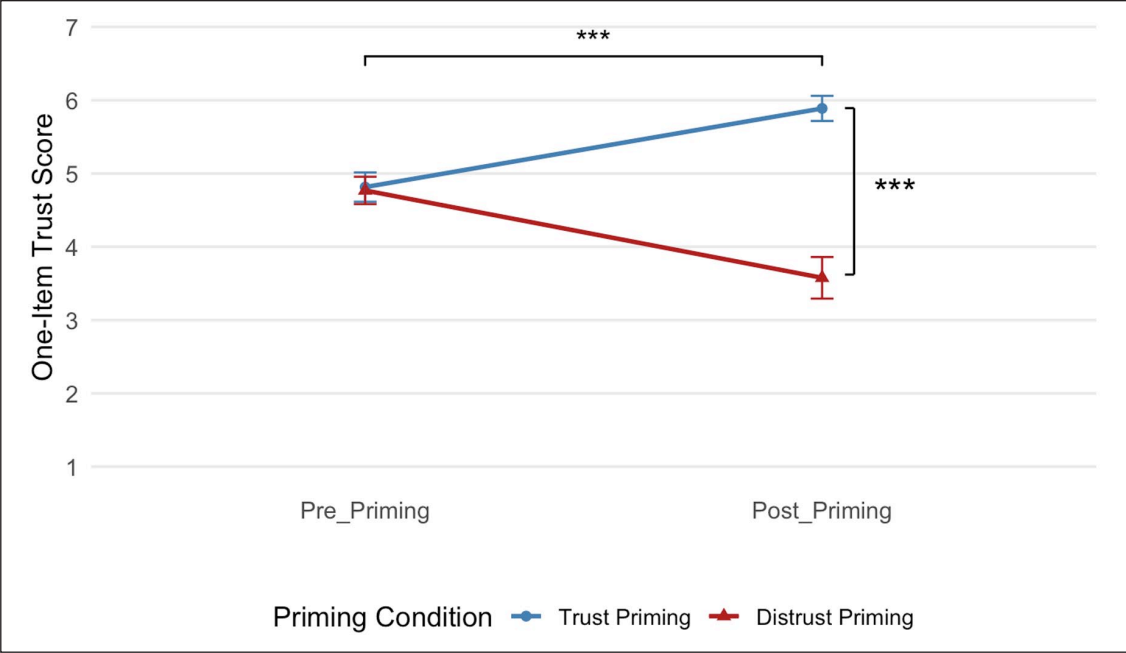


Figure 1. IS one-item trust score before versus after trust priming manipulation.

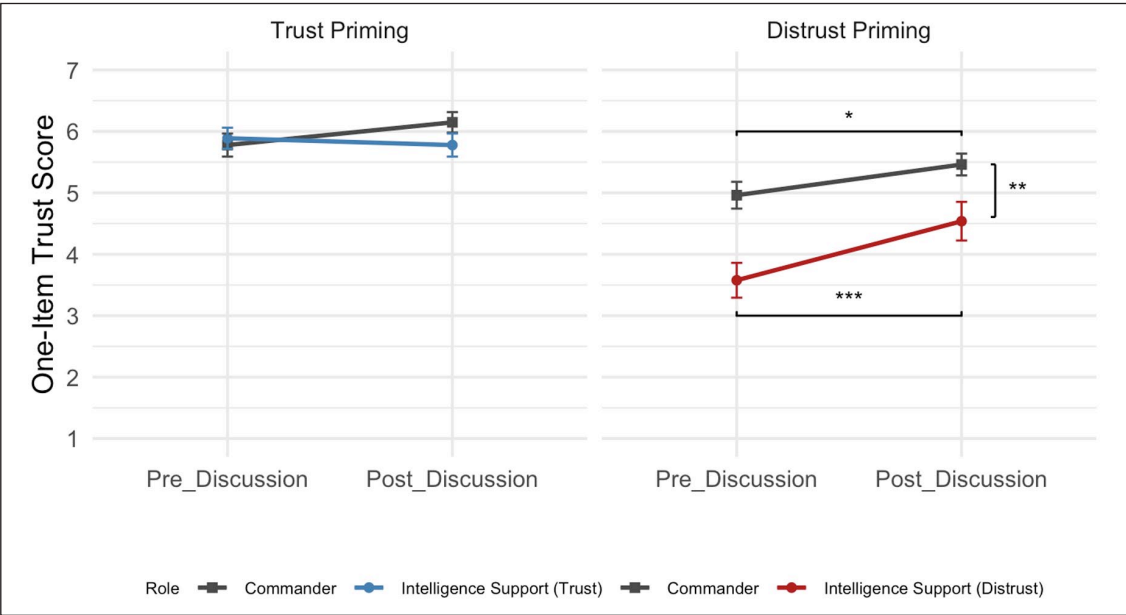


Figure 2. One-item trust score before versus after discussion for each condition.

South—partially confirming H3, but in the opposite direction (see Figure 4).

Conclusion

UAV reliability emerged as the primary determinant of post-task trust, with the priming condition showing no significant effect on post-task MDMT, suggesting that direct

performance experience overrode socially formed attitudes. Pre-task ratings, however, revealed a contagion effect: in the Distrust condition, IS’s trust rose after discussion rather than pulling CO toward distrust, with the CO’s authoritative role conferring disproportionate social influence (Danner-Schröder, 2021; Schilke et al., 2015). IS’s brief priming may not sustain social influence from a higher-authority teammate compared to extended hands-on training (Körber et al.,

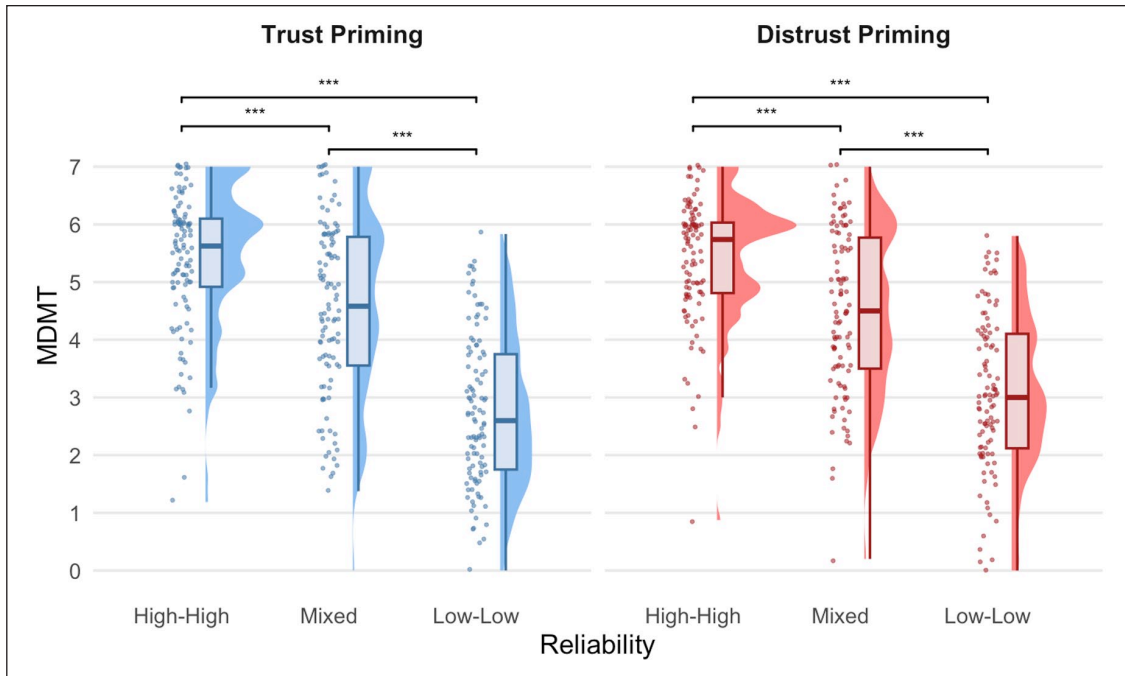


Figure 3. Trust contagion: MDMT across reliability levels in each condition.

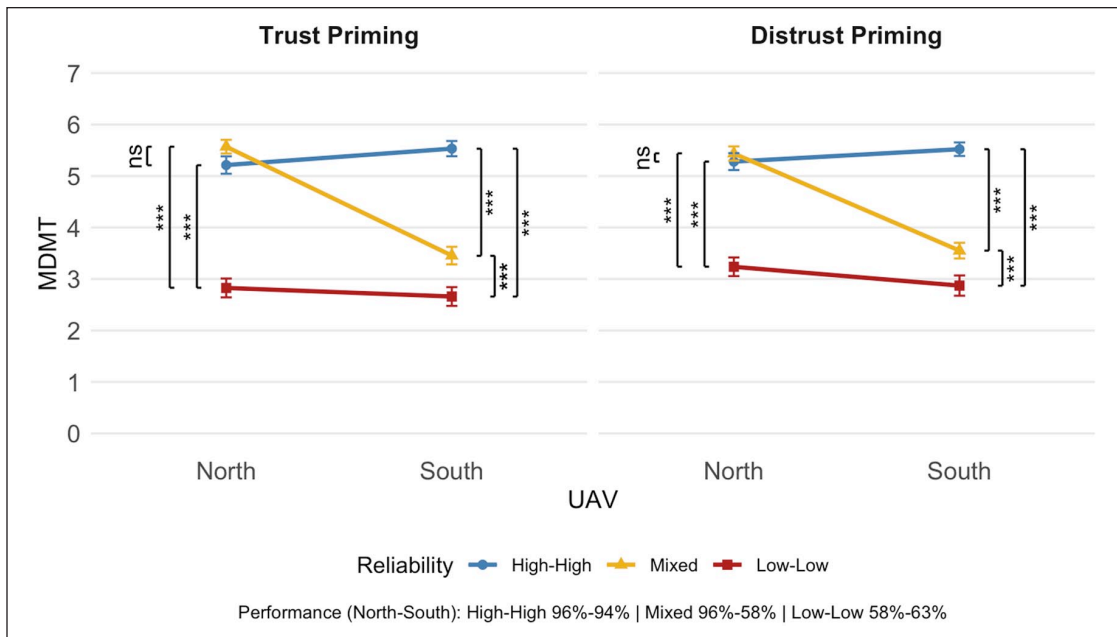


Figure 4. Trust transfer: MDMT across reliability.

2018; Sauer et al., 2016). Naturalistic conversation further provided weaker influence than confederate-scripted interactions (Rojas et al., 2025). These findings diverge from prior contagion studies where social influence propagated via explicit trust exchange (Erengin et al., 2025; Hidalgo et al., 2025; Rojas et al., 2025), highlighting power dynamics as an alternative contagion mechanism. Team hierarchies may

suppress lower-authority operators' authentic doubts about system reliability, a training and team-design concern for safety-critical operations.

Trust transfer occurred in the positive direction, opposite to the negative SWT predicted by H3. In the Mixed condition, the reliable North elevated trust in the less reliable South despite its lower actual performance, likely because

the “algorithm training” framing positioned errors as correctable, with North’s strong performance generating a halo effect (Nisbett & Wilson, 1977) rather than downward contamination from South. Together, these findings underscore that role hierarchy, training format, and task characteristics collectively shape trust dynamics in multi-human multi-agent teams. Future research can systematically vary these factors to clarify their effect in non-dyadic HATs.

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