

Predicting Trust Contagion via Gaze Allocation in Multi-Human-AI Teams

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Emanuel Rojas¹  and Mengyao Li¹

Abstract

In multi-human–AI teams, trust in AI is shaped not only by direct interaction but also by social influence among teammates, a process known as trust contagion. While social signals facilitate this process, prior research have overlooked specific mechanisms such as gaze. This study examined whether gaze allocation, attention dispersion across teammates, task interfaces, and the environment, serves as a behavioral indicator of trust contagion. Results showed that gaze allocation varied with both AI reliability and a confederate's trust level. When AI performed poorly, participants paired with a high-trusting confederate showed more concentrated gaze, while those paired with a low-trusting confederate displayed greater dispersion, reflecting more frequent scanning for information and verification. Gaze predicted AI trust non-linearly, with moderate gaze associated with higher trust, suggesting both overly narrow and scattered gaze limit effective information processing. These findings highlight gaze allocation as a key nonverbal mechanism through which trust contagion unfolds.

Keywords

human-AI teaming, trust in AI, gaze analysis, social signal processing

Introduction

In multi-human–AI teams, where multiple human teammates work alongside AI teammates, trust in AI is not formed solely through direct interaction but is shaped through social influence among human teammates (Guo et al., 2023). Humans can consciously and unconsciously provide social information that affects others' perception of and behaviors toward the AI, a process we defined as *trust contagion* (Rojas et al., 2025). Understanding trust contagion is crucial because trust in AI directly influences reliance, cooperation, and team performance (Guo et al., 2023). Trust contagion is facilitated by social signals conveyed by other teammates, yet prior research has largely overlooked specific social signals through which trust contagion unfolds, such as gaze. We argue that *gaze allocation* constitutes a key but underexamined mechanism in this process. Gaze provides continuous, nonverbal information about individual's trust (Admoni & Scassellati, 2017). This allows teammates to infer another's trust toward the AI and implicitly calibrate their own trust judgments and cooperative behavior. Despite its relevance, gaze has been largely overlooked as a mechanism for characterizing trust contagion in multi-human–AI teams. Thus, this paper investigated whether a human teammate's expressed trust in AI can influence one's gaze allocation. This addresses whether gaze serves as a behavioral mechanism through which trust contagion unfolds in multi-human–AI teams.

Background

Trust in AI is enacted behaviorally through how individuals allocate attention during interaction (Goubard & Demiris, 2025). In human–automation contexts, trust shapes information-sampling strategies: higher trust reduces uncertainty and the need for verification and monitoring, whereas lower trust or elevated uncertainty increases visual sampling of task- and system-relevant cues (Hergeth et al., 2016; Ries et al., 2025). In multi-human–AI teams, information sampling is further shaped by social context. Individuals infer an AI's capability not only from direct experience but also from trust-related cues expressed by teammates. These social signals can alter perceived uncertainty and reliance, providing a behavioral pathway through which trust contagion occurs. Gaze plays a central role in this process because it operates continuously and nonverbally, revealing what individuals treat as informative or requires monitoring. Prior work in dyadic human–AI interaction has shown that reduced gaze toward automation (i.e., fixations count, backtrack rate) is associated with higher trust (Lu & Sarter, 2019). However,

¹Georgia Institute of Technology, Atlanta, GA, USA

Corresponding Author:

Emanuel Rojas, Georgia Institute of Technology, Atlanta, GA 30332-0002, USA.

Email: erojas9@gatech.edu

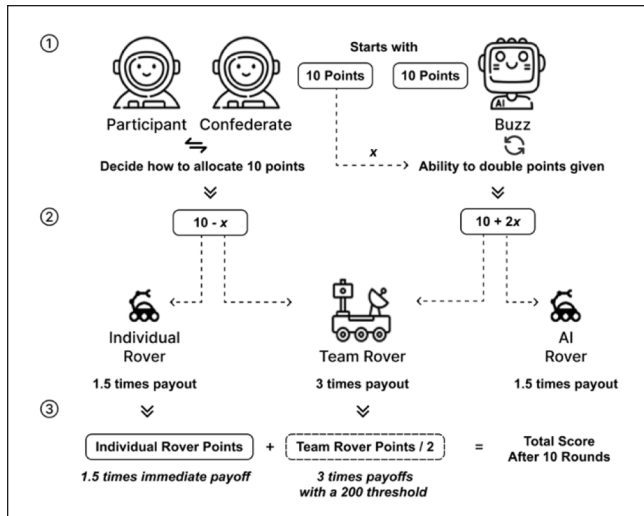


Figure 1. Space rover exploration game.

little is known about how gaze functions as a socially mediated mechanism in multi-human-AI team settings. Gaze allocation may serve as a behavioral indicator of trust in multi-human-AI teams. Specifically, the dispersion and flexibility of attention across teammates may reflect how social influence from human teammates shapes an individual's trust. Reduced gaze allocation has shown to relate to higher levels of trust toward AI teammates within dyadic teams (Ries et al., 2025). This may suggest that individual's gaze allocation can predict their trust levels toward certain teammates. Therefore, this study will investigate the following:

RQ1: Can gaze allocation be influenced by a human teammate's trust levels toward AI through trust contagion?

RQ2: Can gaze allocation predict trust toward human and AI teammates in multi-human-AI teams?

Approach

A team of three, consisting of one participant, one confederate, and one virtual AI teammate, performed a 10-round trust-based game that requires resource allocation and joint decision making, derived from a prior study (Rojas et al., 2025). We designed a 2 (AI reliability: high vs. low, within-subjects factor) $\times$ 3 (confederate trusting: high, low, neutral, between-subjects factor) mixed-subject study. For reliability, the AI teammate performed the task with 100% accuracy rate in the high-reliability condition, and only 60% accuracy for the low-reliability condition. Participants always experienced the same high-low reliability to ensure trust building at the beginning of the experiment. To manipulate the influences of trust contagion, an experimenter was trained to enact three levels of trusting behavior. In the neutral condition, the confederate only commented on the fact-based

game status; in the high-trusting condition, the confederate expressed positive attitudes toward the AI teammate; in the low-trusting condition, the confederate made skeptical comments toward the AI teammate. This design allows us to evaluate how trust contagion spreads from the confederate to the participant across varying levels of AI reliability, and how that contagion manifests in gaze allocation. To assess trust contagion, participants engaged in the Space Rover Exploration game, a trust-based resource allocation task designed to elicit joint decision-making and social interaction with both the confederate and participant.

Space Rover Exploration Game

Developed by combining the trust game and the threshold public goods game, the Space Rover Exploration game demonstrated the conflicts between trusting an AI teammate to achieve a long-term high payoff or relying on themselves for a short-term guaranteed individual payoff (See Figure 1). Participants evaluated this tradeoff and cooperated with their AI teammate, Buzz, to collect points over 10 rounds. Each round began with the participant and a confederate deciding how to divide 10 points with Buzz, who can double the points received. This decision reflects their trust in both Buzz's capability to cooperate in investing points. After allocation, both human players and Buzz independently decided whether to invest their remaining points in the team rover, which offers a high reward ($3\times$ multiplier) but requires a 200-point threshold for the multiplier to activate, or in individual rovers, which provide an immediate yet smaller return ($1.5\times$ multiplier). While the team rover yields greater potential payoffs, it carries the risk of losing all invested points if the threshold is not met by the end of the game. The participant, given the commander role, always makes the final decision in these joint decision-making situations. The main dilemma is whether participants trust Buzz enough to contribute toward activating the team rover by allocating most of their points to Buzz. In rounds 1 to 5, Buzz was programed to consistently contribute all its points to the team rover. However, in rounds 6 and 9, Buzz prioritizes its own rover instead and participants do not gain any points toward the team rover. Participants do not know this information beforehand. Throughout the game, the participant and the confederate continuously discuss and evaluate their trust in Buzz to determine their next steps.

Measures

Participants wore Pupil Labs Neon eye-tracking glasses throughout the experiment while interacting with the confederate. We focused on three visual areas of interest (AOIs): the confederate's face, the task tablet, and the surrounding environment. Gaze allocation was quantified using Shannon entropy, commonly used in studies of gaze during automation interaction (Cui et al., 2024; Ries et al., 2025). First, we

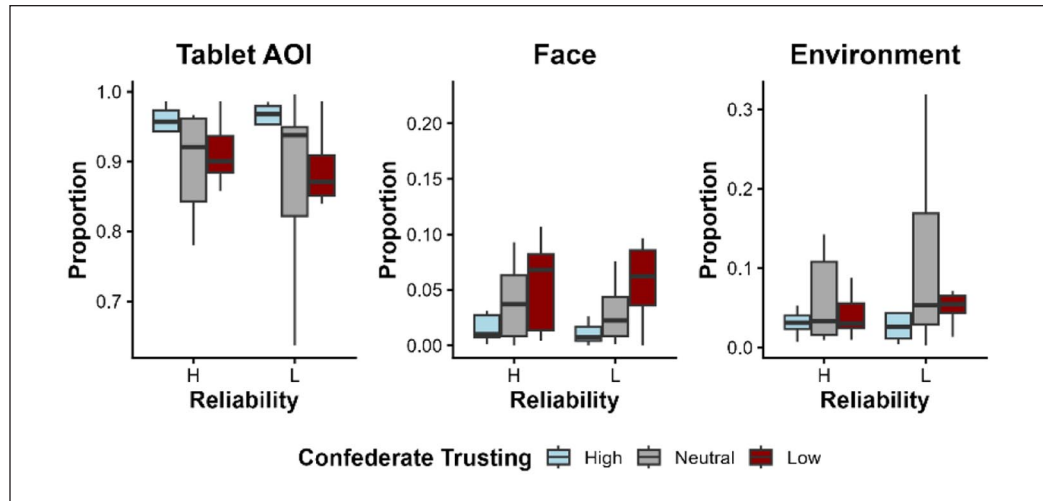


Figure 2. Box plot of gaze proportion by confederate trusting and AI reliability conditions.

calculated the proportion of dwell time spent on each AOI per Reliability condition for every participant. Then, these proportions were used as inputs into the Shannon entropy function to output a gaze allocation score per Reliability condition for every participant. A high gaze allocation score indicates scattered gaze among the three AOIs, while a low gaze allocation score conveys a focused gaze toward one or two AOIs. Trust in the confederate and the AI was measured after Rounds 1, 5, and 10 using an adapted eight-item Multi-Dimensional Measure of Trust (MDMT; Ullman & Malle, 2019), rated from 0 (“Not at all”) to 7 (“Very”), with an additional “does not fit” option.

Participants

A power analysis with $\alpha = .05$ and power of 0.80 was conducted to obtain a sample size of $N = 42$. For each condition, an equal number of male ($n = 7$) and female ($n = 7$). All participants’ ages ranged from 18 to 24 years old. Recruitment was through a participant recruitment platform. The study lasted 30 min. Participants were compensated with one research credit or 10 dollars of their choice. Due to sensor malfunctioning and missing data, the sample size for the gaze data was $N = 29$. The high-trusting confederate condition had $n = 10$, neutral-trusting confederate condition had $n = 11$, and the low-trusting confederate condition had $n = 8$.

Analyses

Data were analyzed via R studio using the *lme4* and *emmeans* packages (Bates et al., 2015; Lenth, 2024). Our analyses were conducted using linear mixed models (LMM) with a pairwise comparison with Bonferroni correction. LMM offers flexibility in modeling individual differences by incorporating random effects. These random effects account for within-subjects variability and dependency

among repeated measures. (Muhammad, 2023). To answer RQ1, we measured gaze allocation where the interaction of *Confederate Trusting* and *AI Reliability* are the fixed effects, with participant ID as the random intercept. This is to measure if gaze allocation can be influenced by a human teammate’s trust levels toward AI through trust contagion. For RQ2, we utilized two models to predict trust in AI and trust in confederate where gaze allocation was the fixed effect and participant ID was the random intercept. These models would demonstrate if gaze allocation can predict trust toward human and AI teammates in multi-human-AI teams.

Outcome

Due to the gaze allocation not satisfying the normality assumption, we performed a square root transformation to satisfy normality. The descriptive statistics of the gaze proportions, prior to the square root transformation, by *Confederate Trusting* and *AI Reliability* are shown in Figure 2. As shown in Figure 3, there was a significant interaction effect between *Confederate Trusting* and *AI Reliability*, $\beta = .07$, $t(282) = 2.79$, $p < .001$, $\omega_p^2 = 0.06$, indicating that the effect of teammate trust on gaze allocation depended on AI reliability. During the low reliability rounds, the high-trusting condition ($M = 0.28$, $SE = 0.06$) had a significantly lower gaze allocation than the low-trusting condition ($M = 0.60$, $SE = 0.10$), $p_{adj} = 0.026$, $d = 1.06$, 95% CI $[-1.86, -0.25]$. This effect suggests gaze allocation becomes more concentrated when a teammate expresses high trust in the AI, particularly under conditions of reduced AI reliability. No main effects were significant, $p > .05$.

To assess whether gaze allocation predicted trust toward AI, we modeled AI trust as a function of gaze entropy, including both linear and quadratic terms. Since the gaze allocation did not show a linear trend, we included the squared term of

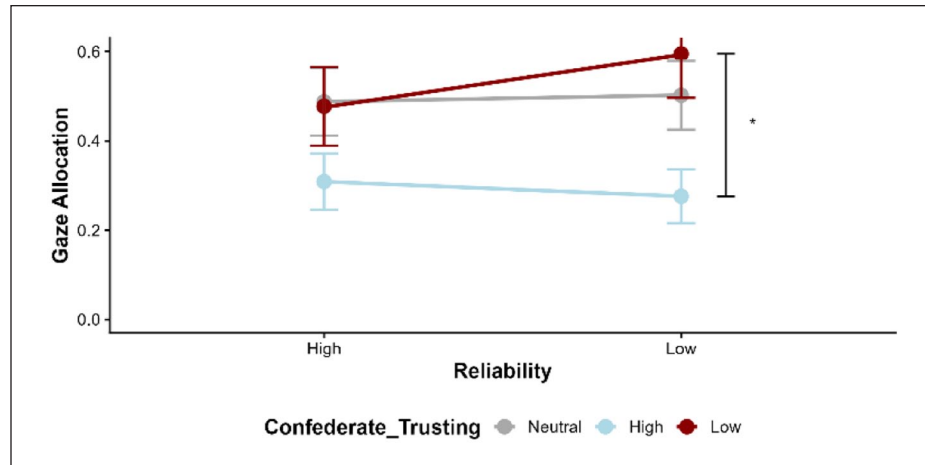


Figure 3. The gaze allocation between confederate trusting and AI reliability conditions.

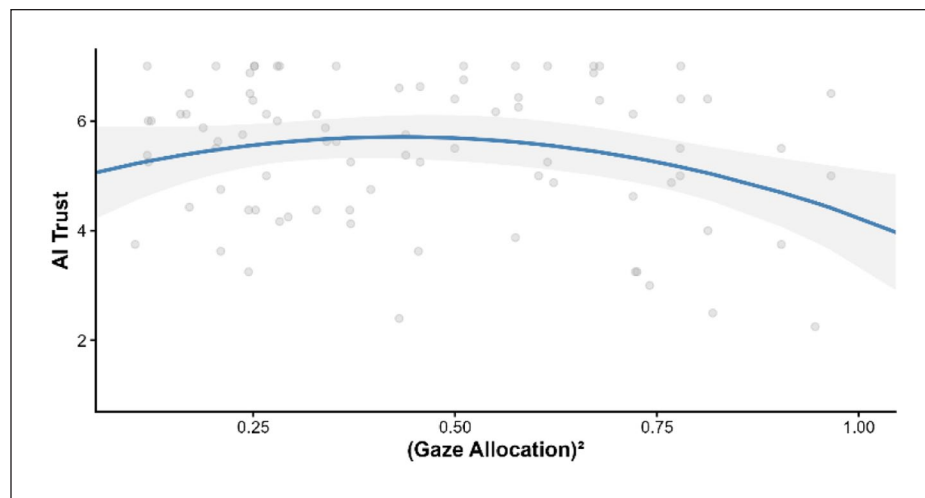


Figure 4. Gaze allocation squared predicting AI trust.

gaze allocation. As shown in Figure 4, there was a significant main effect in the quadratic term of the gaze allocation, $\beta = -4.55$, $t(82) = -2.27$, $p = .026$, $\omega_p^2 = 0.06$, indicating a non-linear relationship between gaze allocation and trust in the AI. This suggests that gaze allocation can predict AI trust, with trust varying as a function of how attention is distributed across information sources rather than a linear trend. For predicting interpersonal trust toward the confederate through gaze allocation, there was no significant main effect, $p > .05$, so no further analyses were conducted.

Conclusion

This study examined how gaze allocation, a measure of attention dispersion across teammates, task interfaces, and the environment, reflects trust contagion in multi-human-AI teams. For our first research question, gaze allocation differed as a function of both AI reliability and the human teammate's expressed trust. When AI performed poorly,

participants paired with a high-trusting confederate showed more concentrated gaze, suggesting reduced need for broad monitoring. In contrast, those paired with a low-trusting confederate showed significantly higher gaze dispersion, indicating more frequent transitions across areas for information gathering and verification. These findings align with prior work showing increased fixation on unreliable automation (Lu & Sarter, 2019) and reduced gaze toward autonomous agents when trust is higher (Ries et al., 2025). Critically, our results extend this literature by demonstrating that such gaze shifts are socially influenced: teammates' trust expressions systematically shape how individuals allocate attention under uncertainty, consistent with a trust contagion mechanism. Future research should examine more dynamic, real-time team settings to further understand how gaze behavior supports the trust contagion process.

For our second research question, we found evidence that suggests gaze allocation serves as a behavioral indicator predicting trust in AI teammates, but in a non-linear manner.

Contrary to studies reporting a simple inverse relationship (Ries et al., 2025), the significant quadratic effect suggests an inverse U relation where moderate gaze allocation is associated with higher trust. This may support balanced gaze to both direct AI cues and teammate-mediated social information which led to the highest trust, whereas narrower or more scattered gaze patterns may limit such information processing. A narrow gaze allocation score may indicate participants are not properly receiving indirect information pertaining to the AI from the teammate, leading to reduced trust. Conversely, scattered gaze allocation may reflect weaker monitoring toward the AI and may lead to not receiving enough direct information. This pattern may be consistent with trust contagion where moderate gaze allocation may facilitate exposure to cues from human and AI, whereas overly concentrated or highly sporadic gaze may limit them. In addition, gaze allocation seems to be broadly consistent with prior work that both misuse and disuse can be problematic in trusting the AI (Parasuraman & Riley, 1997). Future work should test whether this inverted-U pattern generalizes to other human-AI teaming contexts, including more complex multi-human, multi-agent settings.

This study has two main limitations. First, the small sample size due to missing and malfunctioning data has reduced statistical power and affected the reliability of the findings. Future studies should recruit larger samples to replicate these effects. Second, the decision-making task was relatively static and did not require rapid visual scanning. More dynamic tasks, such as search-and-rescue scenarios, may elicit richer gaze-transition patterns and more clearly reveal the relationship between attention allocation and trust dynamics. Future work should employ more dynamic task settings and consider including AI itself as a distinct visual area of interest to better capture real-time gaze behavior.

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Declaration of Conflicting Interests

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ORCID iD

Emanuel Rojas  <https://orcid.org/0009-0003-9979-0013>

References

- Admoni, H., & Scassellati, B. (2017). Social eye gaze in human-robot interaction: A review. *Journal of Human-Robot Interaction*, 6(1), 25. <https://doi.org/10.5898/jhri.6.1.admoni>
- Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting Linear Mixed-Effects Models Using lme4. *Journal of Statistical Software*, 67, 1–48.
- Cui, Z., Sato, T., Jackson, A., Jayarathna, S., Itoh, M., & Yamani, Y. (2024). Gaze transition entropy as a measure of attention allocation in a dynamic workspace involving automation. *Scientific Reports*, 14(1), 23405.
- Goubard, C., & Demiris, Y. (2025). Cognitive modelling of visual attention captures trust dynamics in human-robot collaboration. *ACM Transactions on Human-Robot Interaction*, 14(4), 67:1–67:21. <https://doi.org/10.1145/3732795>
- Guo, Y., Yang, X., & Shi, C. (2023, July 10). *Enabling team of teams: A trust inference and propagation (TIP) model in multi-human multi-robot teams*. Robotics: Science and Systems XIX. <https://doi.org/10.15607/RSS.2023.XIX.003>
- Hergeth, S., Lorenz, L., Vilimek, R., & Krems, J. F. (2016). Keep your scanners peeled: Gaze behavior as a measure of automation trust during highly automated driving. *Human Factors*, 58(3), 509–519. <https://doi.org/10.1177/0018720815625744>
- Lenth, R. (2024). *emmeans: Estimated Marginal Means, aka Least-Squares Means* (version 1.8.9) from CRAN
- Lu, Y., & Sarter, N. (2019). Eye tracking: A process-oriented method for inferring trust in automation as a function of priming and system reliability. *IEEE Transactions on Human-Machine Systems*, 49(6), 560–568. <https://doi.org/10.1109/thms.2019.2930980>
- Parasuraman, R., & Riley, V. (1997). Humans and automation: Use, misuse, disuse, abuse. *Human Factors*, 39(2), 230–253. <https://doi.org/10.1518/001872097778543886>
- Muhammad, L. N. (2023). Guidelines for repeated measures statistical analysis approaches with basic science research considerations. *The Journal of Clinical Investigation*, 133(11), e171058.
- Ries, A. J., Aroca-Ouellette, S., Roncone, A., & de Visser, E. J. (2025). Gaze-informed signatures of trust and collaboration in human-autonomy teams. *Computers in Human Behavior: Artificial Humans*, 5, 100171. <https://doi.org/10.1016/j.chbah.2025.100171>
- Rojas, E., Hsu, D., Huang, J., & Li, M. (2025). Interpersonal influence matters: Trust contagion and repair in human-human-AI team. *Computers in Human Behavior: Artificial Humans*, 5, 100194. <https://doi.org/10.1016/j.chbah.2025.100194>
- Ullman, D., & Malle, B. F. (2019). Measuring Gains and Losses in Human-Robot Trust: Evidence for Differentiable Components of Trust. *2019 14th ACM/IEEE International Conference on Human-Robot Interaction (HRI)*, 618–619.