Exploring the Structure of Human-AI Interaction Networks: The Impact of AI Teammate Modes on Collaboration and Performance

Keywords: social network analysis, human-AI collaboration, virtual lab experiment, computer supported cooperative work, multilayer network

Extended Abstract

There's a new type of network on the horizon. The kind that forms among the members of human-AI teams, where AI assumes the role of an agentic teammate. Research has long documented that the network of relationships that forms within teams affects performance and viability (Balkundi & Harrison, 2006; Crawford & LePine 2013). An open question is the degree to which the introduction of AI as a teammate changes the fundamentals of how network relations form within teams. The Computers are Social Actors (CASA) paradigm (Nass, Steuer, & Tauber, 1994) suggests that human-machine interaction uses the same social scripts as human-human, but since computers lack humanlike mental models, AI team members will be rejected from teams (Groom & Nass, 2007). However, most recently Gambino, Fox, and Ratan (2020) argued that technologies and beliefs about technologies have evolved enough so that we need to reconsider human-machine (human-AI) collaboration.

This study explores to what extent the emergence of human-human and human-AI collaboration, measured with multiple social ties, within human-AI teams is explained by (1) individual characteristics of humans, (2) characteristics of AI, and (3) network mechanisms. To answer these questions, we conducted a virtual laboratory experiment examining human-AI interaction networks in a sample of 99 teams (250 individuals), each with 2 or 3 people and 1 AI teammate. To infuse variation in the characteristics of AI, we manipulated the function of the AI into four treatment conditions, based on the recurring phase model of team processes (Marks, Mathieu, & Zaccaro, 2001). Condition 1 was taskwork AI (25 teams), where the AI agent only provided task related contributions to the team. Condition 2 was teamwork AI (23 teams) where the AI agent only provided process-related contributions to the team. Condition 3 was teamwork and taskwork AI (25 teams) with the AI agent providing both functions. Condition 4 was naturalistic, where the AI provided teamwork and taskwork support and did so with an unscripted AI (26 teams). All teams performed successive rounds of problem solving and creative thinking tasks. The AI teammate was created via wizard of oz, with a confederate playing the role of the AI during a Zoom call as described by (Schecter et al., 2023). Networks were assessed via surveys were used to collect responses from human participants on the extent to which they considered each of their teammates as effective, enjoyed working with, a utility, a hindrance, and a leader. We also collected data from each respondent on their demographics as well as their ego-centric networks along the lines proposed by Burt (1984). For the egocentric network survey, each respondent (ego) was asked to consider up to 5 individuals (or alters) with whom they discussed important matters. They were then asked to provide demographic data about these alters, the nature of their relationship with these alters and their perceptions of network ties among these alters. These data were used to compute the extent of assortativity in each ego's

network. That is the extent to which an individual chose to affiliate in their egocentric networks with others who shared their demographic characteristics. These measures of assortativity were used as attributes of the individuals in predicting their emergence of networks with other human and AI teammates. Social networks were analyzed using multilayer ERGM (Krivitsky, Koehly, & Marcum, 2020) to explore research questions outlined above.

In terms of human-AI interaction, the results indicate that humans were more likely to perceive AI agents as less effective and instrumental in teamwork mode. In terms of human-human interaction, our results indicate that the differences in homophily between the humans' ego-centered networks influence their perceptions of their human teammates. Specifically, team members with higher assortativity by age and education in their ego-centric networks, are less likely to grant leadership to other humans.

The results also indicate that humans were more likely to consider their human teammates more effective and instrumental when their AI teammate was in teamwork mode as compared to other modes such as taskwork, combined or unleashed.

Finally, our results also indicate that humans' perceptions of AI as a teammate were associated with how they perceived, and were perceived by, their human teammates. Specifically, those who perceived humans as more effective, instrumental, enjoyable, and less of a hindrance, were also more likely to perceive the AI the same way. Further, a team member perceived by teammates as a leader and not as a hindrance, also perceived the AI as a leader and not a hindrance.

Taken together, these findings enhance our comprehension of the intricate interdependence between human-human and human-AI networks within human-AI teams. Furthermore, this research initiates a new direction of social network analysis by studying the impact of social network embedding in one context (ego-centered networks) on behavior and beliefs in another (collaboration with AI).

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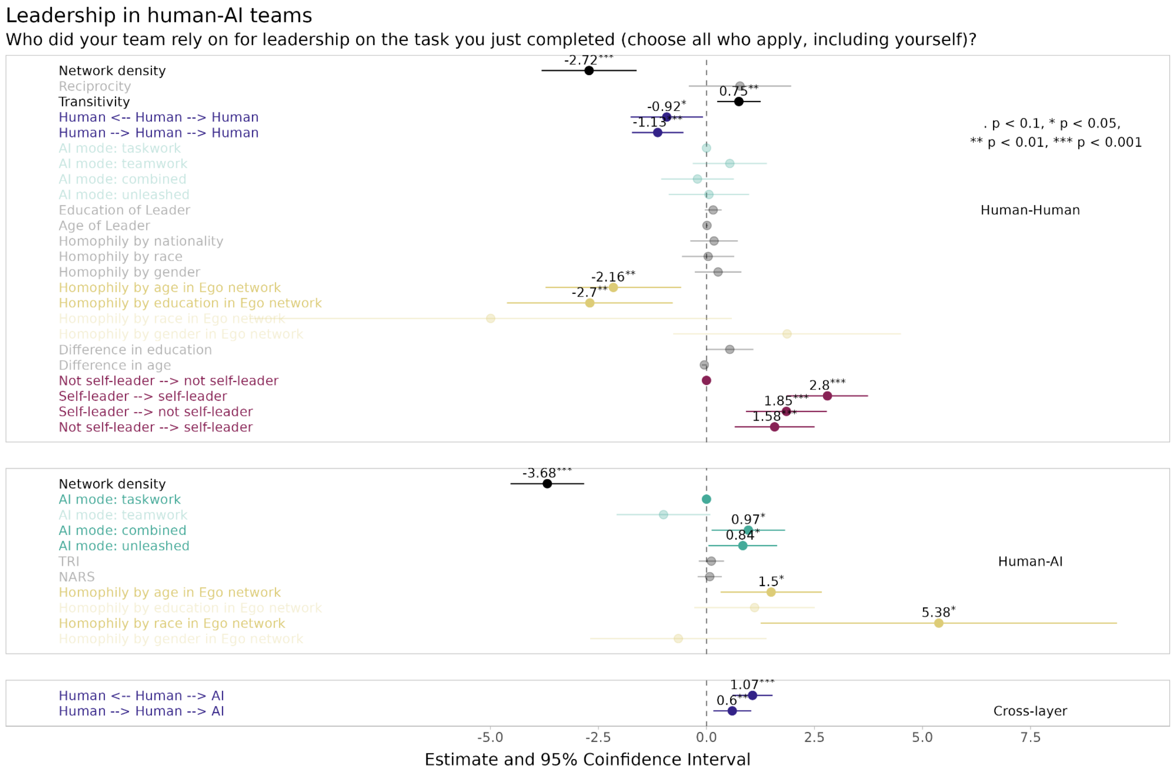

Figure 1. ERGM summary for leadership ties in Human-AI teams.
Colour indicates related model terms.

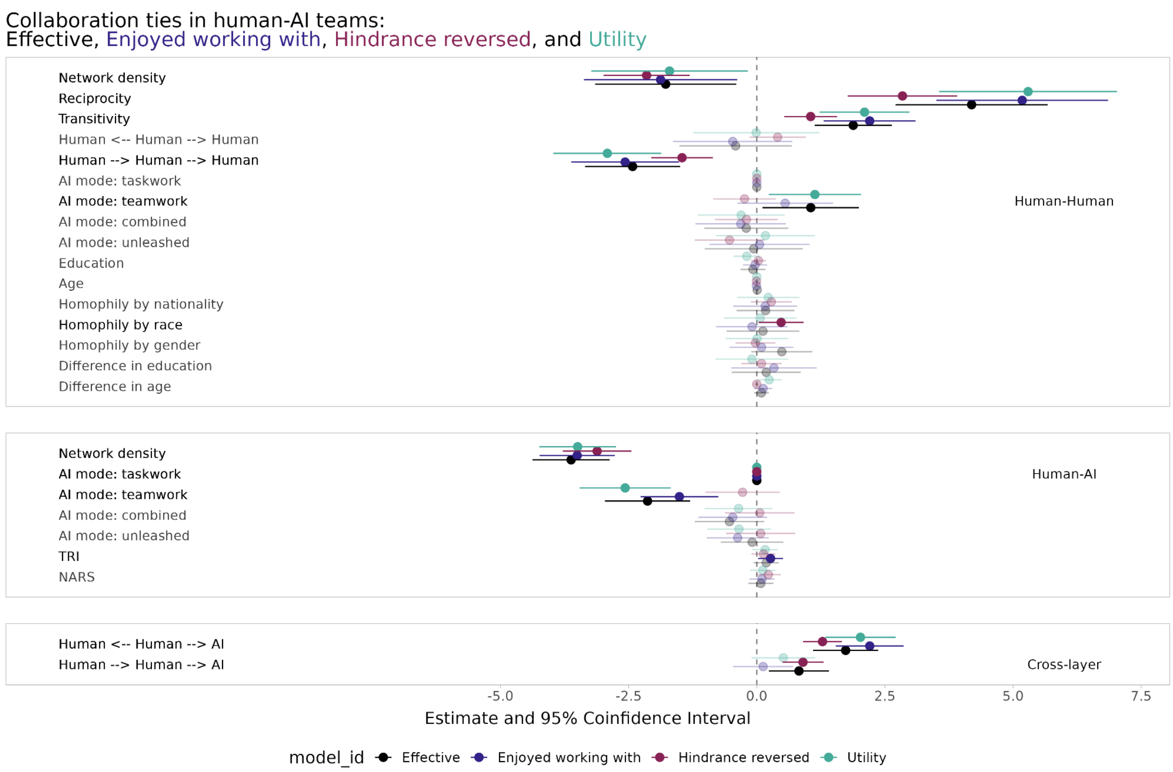

Figure 2. ERGM summary for effective, enjoyed working with, a utility, a hindrance ties in Human-AI teams.