Analysis of Social Signals in Human-Robot Action Teams

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ABSTRACT

Action teams, such as emergency medical teams, are a unique type of team where people work in time-critical contexts under uncertainty. Effective communication and coordination is essential to ensure positive outcomes for these teams, and social signals play a crucial role in this process. Therefore, robots must be able to interpret and express appropriate social signals to effectively communicate with teams and promote the robot's acceptance as a teammate. We conducted a study where we explored the effect of robot initiative on action team dynamics. We analyzed the behavioral data collected to identify social signals and the associated social behaviors exhibited by the teams. Our findings revealed social behaviors such as emergent leadership (where one team member took over team and task coordination), othering of the robot (which resulted in the robot being treated as an outsider), and team camaraderie (which improved connection between the team members). This work will support future robot design that capitalizes on the interpretation and incorporation of these social signals to generate effective teaming behaviors.

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Figure 1: Our work aims to design robots that can support action teams and contribute to the advancement of team goals. We explore this within the context of escape rooms using Stretch, a mobile manipulator robot. From left to right clockwise: Stretch interacts with participants in an icebreaker session, participants solve a puzzle and the robot hands over an item they need, Stretch describes to participants safety considerations while administering first aid.

1 INTRODUCTION

Collaborating and working in teams is a key aspect of human behavior. People get together socially to play sports, indulge in philosophical discussions, or explore new places. Social collaboration is also a crucial part of teams that work in environments such as schools and hospitals. Factors such as communication, coordination, and interdependence among team members play an important role in contributing to successful social collaborations [25].

Increasingly, robots are being designed to collaborate in groups and teams [2, 8, 12, 28] for contexts such as manufacturing, education, and healthcare [18, 20, 35]. One unique type of group is *action teams* - a team where people have to work under high-pressure situations and make quick decisions under uncertainty. This includes emergency medical teams or search and rescue teams. A robot can support such action teams by performing redundant tasks such as fetching items, or dangerous tasks such as surveying unsafe buildings.

Robot verbal and non-verbal behaviors in groups have been shown to contribute to more balanced participation [11, 30], higher group performance [3, 30], and improved trust among teammates [29]. However ineffective robot behaviors can also negatively affect task performance [17] and result in loss of trust in the robot [10]. This can be particularly problematic in action teams since their tasks are time-sensitive and critical, and failures can be costly. Therefore, we need to specifically understand how different robot behaviors can affect action team dynamics.

In this paper, we focus on the social behaviors that emerged as teams interacted with a robot that displayed different levels of robot initiative.

We recently conducted an experiment where groups of three people worked with a robot to solve two escape rooms [14, 15]. The escape room scenarios were designed to imitate the time-sensitive nature of action team tasks and encourage collaboration among members to solve different tasks [7]. In this work, we focus on the analysis of the behavioral data collected as a part of this study.

Our analysis is ongoing, but our findings thus far revealed that specific social cues in human-robot action teams reflected social behaviors such as emergent leadership, othering of the robot, and team camaraderie. Our work contributes to human-robot teaming in two ways. First, it provides insights into the role of social cues and signals in dynamic contexts for human-robot action teams. Second, it can lead to the design of robots that can interpret and contextualize social cues and signals exhibited by human teammates to generate effective teaming behaviors.

*Both authors contributed equally to this research.

2 METHODOLOGY

We designed our experiment [14] to study the effect of robot proactive vs. passive behavior on team performance and dynamics, and how it affected their perceptions of the robot. The experiment was a 2 (escape room games) x 2 (proactive robot, passive robot) within-subjects design, counterbalanced between the conditions to avoid order and game effects. We used a constrained Wizard of Oz [23] methodology to control the robot's speech and behavior during the study.

2.1 Experiment Design

In the passive condition, the robot only communicated or acted when a participant initiated interaction or requested help. In the proactive condition, in addition to complying with human requests, the robot took the initiative to contribute to the task progression through speech and actions.

Each escape room was designed to have three tasks and be completed within 20 minutes. The three tasks were set up to be consistent across both rooms and involved finding objects, solving riddles, and completing challenges to move on to the next step. The medical-themed escape room required the participants to act as an emergency response team and administer care to a mannequin patient. In the hazard cleanup escape room, participants had to perform actions to imitate cleaning up a chemical spill and securing the area.

We recruited 15 participants (seven identified as women and eight identified as men). Participants were assigned to ad-hoc groups of three based on individual availability. In total, five groups of three participants worked with a robot to solve two escape rooms. Group 4 successfully completed both escape rooms, whereas the remaining four groups solved only one escape room.

We collected video data of participants using 10 Mevo Start [1] cameras installed around the room. Participants also wore wireless lapel microphones to capture their speech.

2.2 Data Analysis

We performed a microethnographic analysis [27] of the video data across all teams and conditions. As a part of this process, for each video, two out of three researchers created detailed annotations of the escape room events on a second-by-second basis. In addition, the annotations included audible and visible social cues expressed by the participants, as well as the robot, such as facial expressions and gaze behaviors, speech and non-speech vocalizations, turn-taking, and proxemics.

We then performed a reflexive thematic analysis (RTA) [4, 5] on the annotations. Three researchers first individually conducted open coding of the annotations. Then they iteratively discussed their findings to refine their codes into prominent themes. These themes comprised social behaviors observed through the social signals and cues displayed by the team as they collaborated to complete the escape room tasks.

We did not calculate inter-rater reliability in line with RTA methodology that relies on "researcher subjectivity as a resource for knowledge production" rather than coding consensus [5]. This also aligns with most qualitative research published in the HCI/CSCW communities [19].

Figure 2: After Group 5 unlocked the spill kit with the robot's help, G5P1 took the initiative to hand over the spill sock to their teammates and directed them towards the next step of the task.

3 FINDINGS

We are still in the process of analyzing our data from the experiment, but we present some initial findings with some key examples from teams.

3.1 Leadership

One of the social behaviors that emerged during the study across several groups was leadership. A leader is defined as an individual who influences and focuses their followers towards a mission causing the followers to willingly expend energy in a coordinated effort to achieve that mission [36]. In our study, leadership appeared as one person emerging as the primary communicator and task director within the team. The leader assigned tasks to teammates (including the robot), showed inclusive behavior towards their teammates, and updated the team about task steps and status.

While leadership was expressed through verbal and non-verbal behavior, we also observed non-verbal social cues from teammates that suggested acceptance of an individual's leadership. These included gaze behavior, focus of attention, and movement patterns.

3.1.1 Group 5. G5P1 expressed their leadership through a combination of speech and social cues such as gestures, movements, and actions throughout the task. G5P2 and G5P3's responses to G5P1's lead took the forms of non-verbal behaviors such as supporting a) gaze (e.g. sharing focus of attention), b) actions, and c) movement.

For example, G5P1 set the team up for progress on the next goal by handing each team member a spill sock (See Figure 2). They then directed the next step for the team to do as a whole - G5P1: "Alright, everyone has a spill sock. Let's go put that on the contamination spill." Similarly, G5P1 assessed their current task as done and moved towards the wall to pick up a clue. G5P1 then looked and smiled at G5P2 and G5P3 to share their assessment - "Alright. It looks like it's good enough." Similarly, G5P1 also took the initiative of assigning tasks to the robot or ensuring another teammate coordinated with the robot by making relevant requests to it.

During both these times, G5P2 and G5P3 did not verbally respond to G5P1, however, they both moved towards G5P1. In these instances, G5P2 and G5P3's silence can be perceived as *interactive* *silence* [33]. Interactive silence can be used as a sign of respect, or as a way to draw attention to other non-verbal behaviors. G5P2 and G5P3's following of G5P1's instructions through a combination of non-verbal social cues can thus be construed as acceptance of G5P1's leadership.

Figure 3: G3P3 displays othering behavior towards the robot by expressing mocking laughter in response to Stretch's slow and imprecise movements while picking up a block.

3.1.2 Group 3. G3P3 took the initiative to direct G3P1 and G3P2 to do specific tasks that contributed to the overall task progress. G3P3 took the lead on reading the instructions out loud, and directing their teammates' attention to relevant objects through illustrators like pointing and sharing their focus of attention through gaze. This was eventually followed by G3P3 looking and pointing at individual teammates while providing specific task assignments.

Later, the team had to ask Stretch to scan barcodes to reveal numbers. G3P3 addressed their teammates - "He (G3P2) asks Stretch to read the barcode and you (G3P1) write on the whiteboard for every single block, and I'll look for the spill kit." G3P3 pointed to each individual, object, and the robot as G3P3 referred to each of them while holding both G3P1 and G3P2's attention.

Similar to Group 5, G3P1 and G3P2 did not verbally respond to G3P3's instructions. However, both G3P1 and G3P2 immediately did as G3P3 instructed thus showing their acceptance of G3P3's leadership.

3.2 Othering of the robot

Another social behavior that we observed across several groups was participants *othering* the robot. Brons [6] defines othering as "the simultaneous construction of the in-group and the other or out-group [. . .].. through identification of some desirable characteristic that the in-group has and the other/out-group lacks and/or some undesirable characteristic that the other/out-group has and the self/in-group lacks." Participants expressed othering through non-verbal social cues such as proxemics (grouping) and gaze behavior.

3.2.1 Group 4. Members of Group 4 used phrases such as "Hey, buddy" to refer to the robot, which suggested infantilizing behavior towards the robot. At another time when the robot offered its help after recovering from a technical failure, G4P3 responded with "just sit there and look pretty." This suggests condescending and ostracizing behavior towards the robot. G4P3's response was followed by laughter from teammates. In this situation, this non-linguistic vocalization of the team can be considered as mocking the robot for its inability to contribute or its lack of importance to the team.

Other non-verbal behaviors by the human teammates that contributed to the robot's status as an out-group member included pointing at the robot as they discussed its behavior, non-linguistic vocalizations such as laughter, and illustrators such as sneering while discussing their preference for the robot behavior.

3.2.2 Group 3. We observed that Stretch's imprecise and slow behavior in retrieving the block resulted in Group 3 demonstrating othering behavior towards it. When Stretch said "I found something" while slowly moving towards the block to pick it up but it still had not yet picked up the block, G3P3 laughed and shared an incredulous and amused look with G3P2 (See Figure 3). Even though the team could have engaged in other tasks while Stretch proceeded to pick the block, the team instead continued to visually monitor Stretch's movements while repeating their instructions until it finally brought the block back to the table. The team also engaged in verbal vocalizations like "Oh my god" or non-verbal vocalizations like laughter and sneering in response to its movements.

The combination of G3P3's shared reaction at the robot with the team's continuous monitoring of the robot reveals their distrust in the robot's capabilities. It also reveals their belief that Stretch required their instructions to achieve the pick up task successfully.

3.3 Camaraderie and Rapport

We observed camaraderie and rapport between the humans in the group as well as between the humans and robot. We define camaraderie and rapport as a dynamic structure of three interrelated components: mutual attentiveness, positivity, and coordination [31]. Camaraderie was observed through vocal communication, as well as non-verbal cues such as huddling and laughter.

3.3.1 Group 4. Group 4 demonstrated numerous behaviors including laughter, equal turn-taking, and forgiveness of mistakes that contributed to their overall camaraderie. When the group unlocked the box that contained the knee braces, G4P3 picked up both knee braces. G4P2 read the instructions and realized that one of the knee braces was toxic. G4P3 threw the knee braces back in the box and the team laughed together. Even though G4P3 had erroneously picked up the knee braces, the team didn't engage in accusatory behaviors, forgave the mistake, and laughed about it. The team then successfully proceeded to apply the knee brace. Forgiveness has been shown to improve decision-making and connectedness between team members [9] which was demonstrated by Group 4's task success. Additionally, we observed that Group 4 team members vocally complimented each other which can increase comfort and a sense of belonging within the team.

3.3.2 Group 1. In one instance for Group 1, the robot's behavior provided an opportunity for the team to build camaraderie and share a laugh. When G1P3 asked the robot, "Can you push this

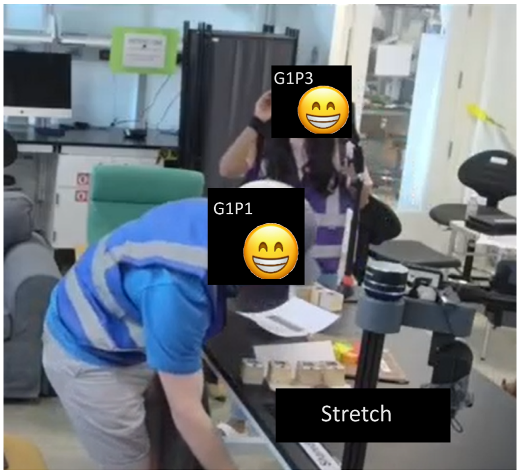

Figure 4: Group 1 laughs together about the robot's abrupt "No" response to the team's request.

cardboard box on the floor," the robot responded with a "No" clarifying its inability to do so. However, this led to a light moment in the team as they joked about the robot's refusal to help. G1P3 laughed and moved further away from the robot and exchanged a glance with G1P2 who said, "I love the way he [says] no." This shared amusement at the robot's behavior (Figure 4), which is still appreciative of the robot, suggests a moment of team camaraderie inclusive of the robot.

4 DISCUSSION AND FUTURE WORK

In action teams, people coordinate in dynamic and time-critical environments. In our study, we observed five teams of three people and a robot coordinate in a time-constrained manner to complete tasks. While verbal communication played an important role in establishing shared understanding among team members, we observed that social signals and cues (e.g. gaze direction, non-verbal vocalizations) and behaviors (e.g. leadership emergence, camaraderie) significantly contributed to successful team coordination in time-critical scenarios. In such scenarios, the robot's ability to recognize these social cues and behaviors can facilitate seamless team integration and coordination in dynamic environments. This is essential to prevent a robot from negatively influencing team dynamics through inadvertent disruption or facing rejection by the team due to its inability to understand the team's task and collaboration needs.

4.1 Being an Effective Teammate

In our data, we observed that leaders expressed their leadership by assigning tasks to each team member. Additionally, the team leaders were also the most vocal team members. In both Group 3 and Group 5, leaders naturally emerged and were not assigned in advance. We also observed that the other team members in these groups accepted the emerged leader. This is important to consider since the emergence and acceptance of leaders allowed the teams to better coordinate among themselves and achieve their goals. The leader can thus be viewed as an individual who stepped up to fulfill an unspoken team need.

Therefore, future work might explore how a robot can use social cues and current context to identify team leader(s). This can facilitate investigation into whether there are differences in robot behavior design that support the leader(s) in comparison to the rest of the team members.

4.2 Robot Contribution to Camaraderie

We observed group camaraderie through a combination of social cues such as shared laughter and behaviors such as forgiveness and mutual appreciation. Camaraderie can support better team coordination as a result of effective team interaction, mutual trust, and an ability to move forward even when faced with obstacles.

A robot can leverage smile and laughter detection methods [13, 26] to identify moments of camaraderie to ensure that it does not disrupt them with untimely speech or non-verbal social cues. In addition, it is worth exploring how the robot can explicitly encourage camaraderie-building behaviors within the team. For example, prior work has explored how a robotic stand-up comedian can better engage its audience by adapting its jokes and timing based on audience response [32].

While robots may not need to specifically participate in team humor, they can still contribute to camaraderie through positive affirmations and encouragement for team members ("Great job, team").

4.3 Supporting Robot Acceptance as a Teammate

In our data, we observed participants othering the robot either due to its limitations or its inability to convey social cues and signals. The robot could undercut the frustration that participants feel about its limitations and repair their trust by acknowledging its limited capabilities and apologizing for it [16, 21, 37]. Prior work [24] has shown that a robot's efforts to repair trust in an emergency situation through apology and a promise to do better can be effective, but also that the timing of these efforts is crucial to trust repair. There is also an opportunity here to appropriately frame the robot's actual capabilities and set the right expectations for its human teammates. Prior work in HRI [22, 34] shows that expectation framing can help to improve perceptions of reliability and trust of a robot.

Furthermore, it may be worth considering how appropriate multimodal cues, such as displays, robot posture, and signal LEDs, can be generated to communicate the robot's status without disrupting team focus or team interactions. Similarly, social cues can be useful in clarifying the robot's intent with respect to fetching an object or decrypting a specific item. This can add explainability in its behavior which may make the robot's behavior less confounding for the team and lead to higher acceptance of the robot.

Through our ongoing analysis, we will investigate whether there are differences in the social behaviors displayed by the teams over time and between different levels of initiative displayed by the robot. Our work will inform 1) whether and how different robot behaviors impact team dynamics 2) the relationship between observed social signals of human teammates and their preferences for robot behavior, and 3) the design of robots that can leverage human social signals and express multimodal social cues to collaborate effectively in action teams.

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