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Human-Robot Action Teams: A Behavioral Analysis of Team Dynamics

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Human-Robot Action Teams: A Behavioral Analysis of Team Dynamics

A thesis submitted in partial satisfaction of the
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by

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Committee in charge:

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Professor Morana Alac
Professor Kristen Vaccaro

2024

The Thesis of Arthi Haripriyan is approved, and it is acceptable in quality and form for publication on microfilm and electronically.

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Some of the analysis in this work overlaps with "Analysis of Social Signals in Human-Robot Action Teams" by P. Ramaraj, A. Haripriyan, R. Jamshad, and L. D. Riek, which appears in SS4HRI: Social Signal Modeling in Human-Robot Interaction Workshop (HRI), 2024.

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ABSTRACT OF THE DISSERTATION

Human-Robot Action Teams: A Behavioral Analysis of Team Dynamics

by

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Master of Science in Computer Science

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Robots are increasingly being used to support human groups and teams. Action teams (such as in emergency healthcare or disaster response) experience high workloads, must work quickly, and must make decisions under uncertainty. They often perform critical tasks where errors or delays can lead to grave harm. Therefore, robots in these teams must be designed and contextualized to not contribute to errors or interrupt human team workflow. In this study, we conducted a behavioral analysis of human-robot action teams as they collaborated with each other to complete tasks in escape rooms to better understand how a robot's actions influenced intra-team dynamics and how team characteristics affected human-robot teaming. Our findings highlight the importance of robots' functional and social contributions for acceptance within

teams, the adaptive nature of teaming behavior in response to perceived robot capabilities, and the significance of the robot's nonverbal cues in shaping human expectations. These insights offer valuable implications for designing effective human-robot interactions in collaborative environments.

Introduction

Teams play a vital role in how humans work together. They foster collaboration and interdisciplinary work by leveraging diverse expertise to efficiently achieve complex goals. [6,28,71]. Understanding team dynamics is important as they affect performance [9,42], error avoidance [37,62], and team member satisfaction [23,96].

This is particularly important for action teams working in fast-paced settings, such as the emergency department or search and rescue [17,70,74]. Action teams experience high workloads, and must make swift decisions under uncertain conditions. Fostering robust team dynamics is important for action teams to avoid negative outcomes [20,58]. For example, in the operating room, poor team cohesion can lead to patient harm, at least half of which could be avoided through better interpersonal skills [15]. Similarly, in firefighting teams, task cohesion influences accident occurrence [35].

Recently, there has been interest in introducing robots into action teams [56,132]. Researchers that extend human-human action teams research to human-robot action teams found that good teams have common goals, share mental models, engage in clear communication, foster awareness of team members' abilities and roles, and engage in feasible tasks [24,25,44,54,97]. Robots can play an essential role in action teams as they can do tasks that might be difficult for humans or that do not require human-specific skills. For example, following natural disasters, robots have been deployed to examine unstable buildings and locate survivors [115,129].

Given the rapid pace of these teams, there are many opportunities for ineffective or erroneous robot intervention, which can be dangerous for team success, or worse can lead to irreparable harm or even death. A robot can fail due to several reasons, such as: 1) physical errors in its effectors, sensors, etc., 2) performance errors such as failing to register a spoken command in a noisy environment, or 3) social errors such as interrupting a user at an inappropriate time during a conversation [51,133]. These can in turn contribute to team failure [122]. If robots are to effectively support action teams, they must operate carefully, as the costs and risks associated with failure are high.

Adding a robot to a team can affect human-human dynamics within the team such as trust [57], conversational dynamics [120], team inclusion [114], and group cohesion [32]. The roles and actions of a robot team can influence human-human interactions within a team [39]. They can also influence the team's perceptions of the robot and the team's acceptance of the robot as a team member [33]. Another study that used a robot moderator during a three-person collaborative game showed that group cohesion could be actively influenced by the robot based on its behavior [108]. Therefore, to successfully integrate robots into teams, it is important to understand human-robot team dynamics.

Researchers have extensively explored human-robot team dynamics across various contexts, including gaze [89,124], proxemics [99], and leader-follower dynamics [75]. For example, one study investigated how individuals adapt their roles in response to changing capabilities and found that participants who took the lead more often valued the collaboration with the robot more negatively than other participants [123]. Additionally, research on robot responses to human emotions found approaching behavior suitable for fear, sadness, and joy, while moving away was often considered inappropriate [87].

Our work addresses three gaps in the field of studying team dynamics in HRI: First, prior literature on human-robot teams mostly involves dyads, which does not accurately reflect the interaction dynamics that exist within teams of three or more members. Secondly, there is a need to move away from structured tasks to more dynamic processes that will allow us to study team characteristics. Lastly, there is a dearth in the literature on capitalizing on non-verbal behavioral data to understand action team dynamics and how robot behavior influences them.

Therefore, in our work, we explore the following research questions: 1) How do action team characteristics affect how team members interact with and respond to a robot? and 2) How do a robot's actions influence intra-team dynamics?

We conducted a study [56] in which teams of three participants and a robot completed challenges together in two escape rooms. The robot acted in either a proactive or passive manner when supporting the team in each escape room. In the proactive condition, the robot initiated speech and actions to further the team's progress, whereas in the passive condition, the robot only acted when participants explicitly asked for help. We used Reflexive Thematic Analysis (RTA) to analyze teaming behaviors and characteristics from the video and audio data collected.

Our analysis yielded several key insights into human-robot teaming. First, we found that teams displayed othering behavior towards the robot, despite the interdependence between the robot and the team during the tasks. Second, we identified the emergence of leaders, robot managers, and robot mediators to support the team's progress. Third, we observed participants employing workarounds to facilitate collaboration with the robot to account for its limitations. Finally, our study revealed that some participants were confused by the robot's behavior and embodiment, but this also created opportunities for unique interactions when teaming with the robot.

Our work provides insights into how action team dynamics are influenced by robot behaviors. First, our work highlights that a robot's acceptance depends on its ability to contribute in terms of function and sociability. Second, our work explores how people in action teams adapt their teaming behavior to accommodate perceived robot capabilities. Third, our study demonstrates the impact of the robot's nonverbal behavior and embodiment on people's expectations of its capabilities. It also discusses how roboticists can manage these expectations.

Chapter 1

Background

1.1 Human-Robot Teaming

Robots are increasingly playing a supportive role within human groups, spanning diverse fields such as manufacturing [104,126], education [2,4], and healthcare [70,94,100]. For instance, in manufacturing, robots can help with picking and placing in the production lines, welding processes, and parts assembly [104]. In healthcare, they can support overburdened healthcare workers by preparing tools for procedures, delivering items, or supporting people with home health management [40,68,69,77].

Most work on human-robot teams has focused on dyadic interactions, including how factors such as trust [80], turn-taking [83], coordination [48], and shared cognition [16] affect dyadic team performance [27]. However, in many contexts, people are more likely to work in groups, rather than just dyads, both socially such as in museums [110] and shopping malls [107], and professionally, such as in healthcare [17,117] and firefighting [10]. Robots interacting with human groups introduce new challenges [18,34] such as understanding the robot's influence on human-human interactions within the group, which are not extensively explored in the human-robot teaming literature [39].

Prior work on human-robot teams has explored communication [11,89], trust recovery [30,119], coordination [52,53], and cohesion [86,91]. These studies usually involve structured and/or tabletop tasks like building towers from blocks [59,128]. However, it is important to look at *action teams* and how robots can support them because they provide insights into how teams function in dynamic, time-critical situations.

Action teams are teams that work in dynamic and complex environments where mistakes can potentially threaten human life and well-being [60,82]. Examples include emergency medical teams, first responders, and aviation teams [79,121]. A robot may be able to support these teams by taking over dangerous or repetitive tasks, fetching supplies, or finding information. However, in order to be an effective teammate, a robot must be able to support team performance [26,48] and team dynamics [31,120].

Effective coordination in action teams may be further impacted if they are ad-hoc teams, and have no prior experience working together [47,63]. Effective human-human teaming is grounded in team situation awareness [105], team cognition [81,98], and teamwork skills [41,118].

1.2 How Robots Impact Team Dynamics

Robots must be carefully designed to support teams as robots can affect team dynamics. For example, the selective placement of an item by a robot can inadvertently create tension between human teammates, as it may seem to reject one participant, placing them in a vulnerable position [59]. In another study [103], researchers investigated how robot verbal support affected inclusion in collaborative tasks. Groups consisted of two ingroup members, one outgroup member, and one robot to assess the efficacy of robot interventions for aiding the outgroup member. Surprisingly, while the robot's targeted support increased outgroup participation, it also seemed to reduce verbal support from ingroup members.

A specific behavior that can affect team dynamics is robot initiative. Baraglia et al. [5] defines initiative as when a robot should help in human-robot interactions. This is especially important to consider as proactive robots, characterized by their initiative-taking capabilities, can autonomously decide the course of action in human-robot interactions, potentially altering the balance of control over task progress. In contrast, passive robots rely on human input for every decision, ensuring that humans retain complete control over the actions taken. Therefore, understanding the implications of robot initiative on team dynamics is crucial, as it determines the degree of autonomy and influence granted to robots in collaborative settings. This can directly affect team dynamics and perceptions of the robot.

For example, a robot expressing its intent through anticipatory cues significantly increased team efficiency, human safety, collaborative fluency, and fostered positive attitudes towards the robot [88]. Additionally, robots that provide proactive explanations were easier to understand [112] and perceived as more trustworthy [134]. Similarly, people perceive a robot expressing socially-adaptive proactivity as more competent and reliable than a non-adaptive robot [66]. Therefore, proactivity should be considered in robot design to enable robots to better support teaming.

1.3 Methods For Studying Team Dynamics

Team dynamics have been explored through analysis of team behaviors including verbal and non-verbal interactions. Prior work analyzed behavioral data such as body pose [7,36], eye gaze [64], hand gestures such as pointing [65,73], handovers, and grasping [84]. However much of these are analyzed in the context of machine learning and computer vision [76,89,106,116]. While these tools can support the detection of social signals such as the ones listed above, deeper analysis is required to understand how these signals may impact human-robot teams and team attitudes toward the robot.

Additionally, there is a lack of existing literature that explores non-verbal human-robot behaviors in action teams. Behavioral data collected during group collaboration can provide insight into information that might not be obvious or explicit, such as non-verbal communication or group proxemics [74,124]. This is important for action teams as efficient collaboration within action teams relies on the capacity to recognize and react to subtle cues, including non-verbal communication. This enables smooth interactions and effective task execution. For example, in one study that observed ad-hoc anesthesia teams, participants demonstrated familiarity with tasks through nods, looks, and simple gestures, facilitating implicit communication. Team members frequently passed equipment to one another, indicating a shared understanding of their roles [8]. This is important for team coordination and can provide insights for improving team performance.

Video-based behavior observations allow for the exploration of real-time behaviors and interaction patterns, revealing nuances often overlooked by casual observation [125]. For example, one study [67] conducted a frame-by-frame video analysis of human-human handovers and found that transitioning the robot's gaze from the giver's face to the giver's hand enhances perceptions of likability, anthropomorphism, and communication of timing. Thus, this type of qualitative video analysis lends itself to studying group dynamics in a human-robot teaming context and the ability to revisit videos strengthens the analysis process.

Chapter 2

Methodology

We ran a study that examined how proactive robot behaviors affect teams and their perceptions of the robot [56]. The study was a 2 (proactive or passive robot) x 2 (hazard or medical) escape rooms within-subjects design, counterbalanced between the conditions to avoid order effects [49]. We followed a Wizard of Oz [93] design to control the robot's speech and actions, and allowed participants to believe the robot was autonomous.

We collected multiple types of data from interviews, surveys, microphones, and cameras. In this thesis, we focus on a video analysis of the behavioral data. The reader can review Jamshad et al. [56] for other analyses from this experiment. This study was declared exempt by the UC San Diego IRB, under protocol # 803126.

2.1 Participants

We recruited participants through flyers and interpersonal communication. After participants expressed interest in the study, one of the researchers scheduled a Zoom call to explain the process and obtain consent. Participants then provided their availability and were assigned to ad-hoc teams of three. Participants received a $40 gift card as compensation for their participation.

We conducted the study with 15 participants. Seven identified as women and eight as men. Five participants were 18 - 24 yrs., nine were 25 - 34 yrs., and one was 35 - 44 yrs. Four participants were undergraduates, seven were graduate students, three were professionals, and

Table 2.1. Participants' Self Reported First Language.

First Language	Number of Participants
English	9
Spanish	2
Kannada	1
Marathi	1
Chinese	1
Korean	1

Table 2.2. Participants' Self Reported Ethnicity.

Ethnicity	Number of Participants
White/Caucasian	3
Asian American/Asian	6
African American/Black and Hispanic/Latinx	1
Asian American/Asian and Pacific Islander	2
White/Caucasian and Asian American/Asian	1
Hispanic/Latinx	2

one did not specify. For more demographic information on native language and ethnicity, see (Tables 2.1 and 2.2).

2.2 Robot Design

We used the Stretch from Hello Robot [61], a mobile manipulator, with a base for navigation and a gripper for manipulating objects in the environment (Fig. 2.1). It is also capable of audio communication, and we added a Bluetooth speaker to improve audio quality and volume. We added cameras to the gripper and to Stretch's head to improve the situational awareness of the robot operator. We also mounted a tablet with a blinking and smiling face to support interactions with Stretch.

We programmed the Stretch to have preset speech options. These were implemented by adding labeled audio buttons to the control interface built by Ghosh et al. [38], for an operator to

Figure 2.1. We designed an escape room study that used Stretch. It could manipulate objects in the environment and talk to people. It could perform handovers, help find objects, read encrypted data, and help with hazardous tasks.

use while controlling Stretch.

We controlled the robot behaviors based on the study condition - either passive or proactive (Fig. 2.2). In the proactive condition, the robot initiated speech and actions to further the team in their task whenever possible. In the passive condition, the robot only acted when explicitly asked for help by the participants.

2.3 Escape Room Design

We conducted an escape room study to understand human-robot teaming [55,56]. Participants collaborated with the robot in two escape rooms, each made up of three different challenges. Participants followed instructions on how to complete the challenges, which were shared with them in the form of a clue. Therefore, each challenge had a clue associated with it. Each challenge consists of several tasks that the robot and team members must perform to

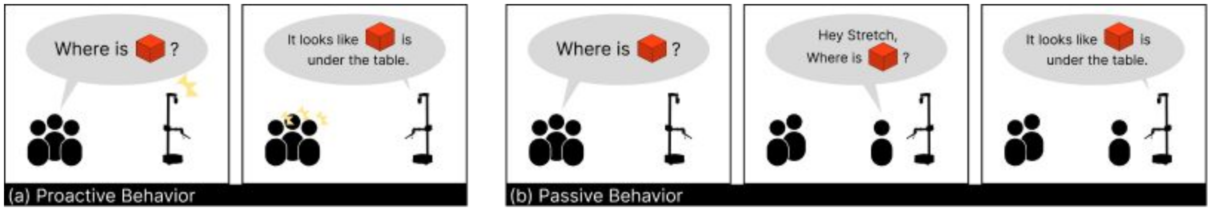

Figure 2.2. Examples of proactive and passive robot behavior. (a): The proactive robot notices the team is stuck, and takes initiative to assist its teammates. (b): The passive robot waits for a human-request before assisting the team.

complete the challenge before they can move to the next challenge in the same escape room. The escape rooms required participants to communicate for effective collaboration because certain tasks could only be accomplished by specific team members identified by the player ID. This was intended to replicate the expertise of different members in for example emergency medicine action teams. The teams were collaborating on a time-constrained task and we hoped that this would replicate the time-constrained nature of real action teams such as firefighters and emergency medical teams.

One researcher interacted with the participants, one teleoperated the robot to act as the participants' team member, and one controlled the camera recordings. We followed best practices in escape room design as described in [21,43].

The escape rooms were designed to be comparable in difficulty and types of tasks to mitigate order effects (Fig. 2.3). One escape room had a hazard cleanup theme in which participants acted as first responders to a chemical spill and had to secure the area. In the second room, participants acted as a medical emergency response team and were required to administer care to a patient mannequin. Tasks were designed to take advantage of unique robot capabilities such as the ability to read QR codes, check for toxins, and fetch items in restricted areas. For more details on the robot and escape room design, please see the appendix of [56].

Figure 2.3. Examples of the Stretch robot supporting the team in the escape room. *Clockwise from top*: Stretch interacts with participants during the icebreaker, participants solve a puzzle and the robot hands over an item they need, Stretch reminds users about safety considerations during first aid.

2.4 Procedure

Participants arrived at the lab and were greeted by a researcher. They were given flyers to introduce them to the robot and its capabilities. They then participated in a short icebreaker activity with the robot to reduce novelty effects.

Next, the researcher explained that the participants would be completing two escape rooms and introduced the general rules and the first room's scenario. Participants entered the escape room and had 20 minutes to complete as many of the three tasks as possible. After 20 minutes, they exited and completed a first round of surveys and interviews. We then introduced the participants to the second escape room and again gave them 20 minutes to complete as many of the three given tasks as possible. They then completed a second round of surveys and

Figure 2.4. Our study lasted 2 hours, and included an icebreaker and two escape rooms, with data collection at key points.

interviews as before. Finally, the researcher debriefed the participants. Overall, the study took a total of 120 minutes, which is summarized in Fig. 2.4.

2.5 Data Collection

We set up ten Mevo Start cameras at various angles around the room with enough overlap to ensure there were no blind spots. We used the Mevo Multicam application to stream and record multiple Mevo cameras at once. We ran the application on two Android tablets. One tablet streamed data from eight cameras which covered areas that were safe for humans to operate in. The other tablet streamed data from two cameras that provided coverage of areas that were unsafe for people to enter, so only the robot could enter these areas.

In the Mevo Multicam application running on the two tablets, we selected view frames from the ten cameras to track people around the room. This resulted in two 20-minute streams for each group tracking the participants in the escape room which were recorded on each of the two tablets.

We collected audio data through wireless lapel microphones, which participants wore around the collarbone for clear voice capture. We recorded microphone data using the Open Broadcaster system [92]. Mevo Start cameras also had built-in microphones but due to ambient noise, data from these microphones lacked clarity, and we only used them as a secondary audio source when needed.

Table 2.3. Example annotations and codes for each of the ELAN tiers.

Tier Level	Annotation	Code(s)
Participant	P3 thanks stretch for bringing yellow block	Robot appreciation
Robot	Robot suggests rereading the clue	Robot speech
Group	P1 and P2 take air purifier out, try to figure out how to turn it on	Task progression, Teamwork

2.6 Data Analysis

We conducted a behavioral analysis of the escape room video data. This method allowed us to gain a more nuanced understanding of social behaviors and human-robot interactions that would have influenced team dynamics and team decisions.

We analyzed ten escape room videos, two from each team. Three researchers performed data coding such that each video was annotated by two coders.

We used the ELAN tool [1] to annotate participants' behaviors and actions. In ELAN, annotations can be organized into different groups, called tiers. We had five primary tiers: Group Behavior, Robot behavior, and one for each participant (labeled P1, P2, and P3). Group Behavior included actions that involved more than one participant (such as group huddles). We identified and annotated verbal behaviors, such as speech, and non-verbal behaviors, including movement, handovers, laughter, gestures, and expressions. Additionally, we recorded relevant information regarding who the interactions involved - individual, robot, participant-participant(s), participant-robot.

We transcribed observed behaviors such as movement and salient interactions such as handovers and nonverbal gestures (Fig. 2.5). Annotations were time-aligned to span the entire behavior observed in the video. Examples of annotations for each of the ELAN tiers and their corresponding code(s) are shown in Table 2.3.

We then analyzed the data using Reflexive Thematic Analysis (RTA) [12]. RTA allows

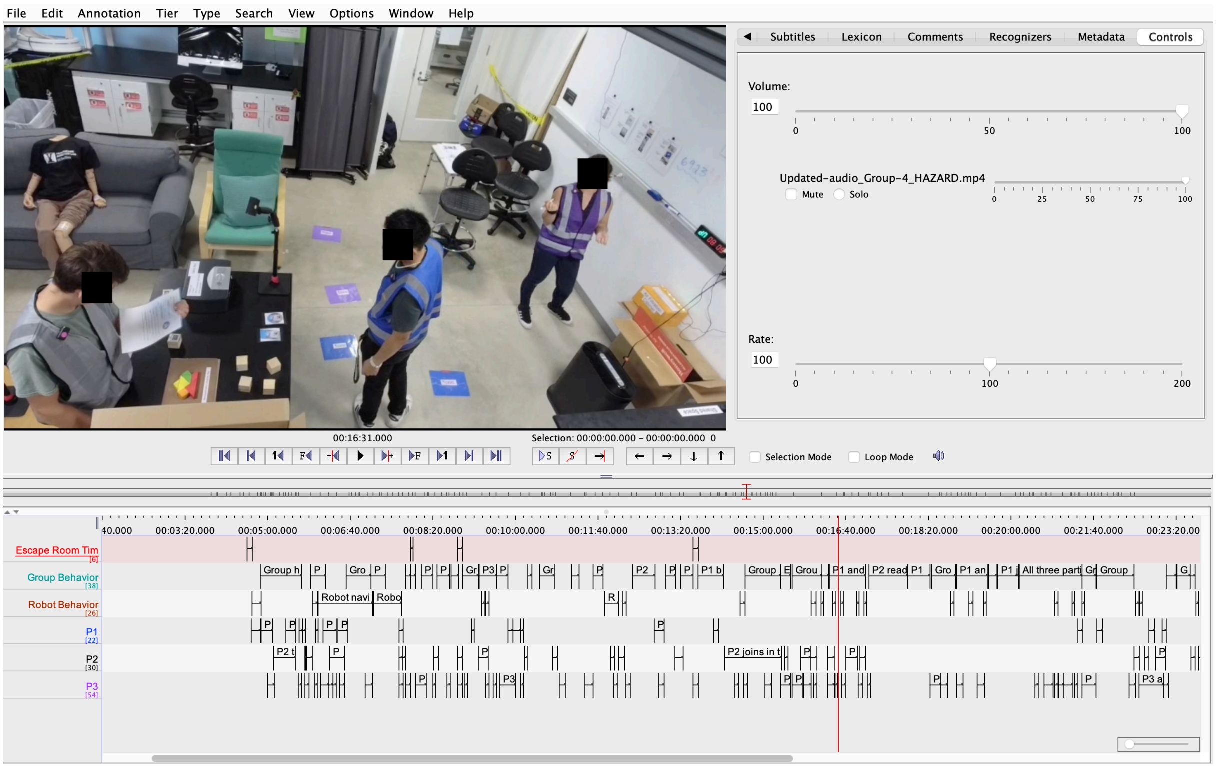

Figure 2.5. ELAN tool used to annotate videos.

for a more dynamic and subjective examination of qualitative data, which is important for understanding both individual and group experiences of the participants [12].

Three researchers first independently coded the data, moving from low-level descriptions to high-level team behaviors. Then we met to iteratively discuss our codes and develop a deeper understanding of the data and observed behaviors. Finally, the researchers refined and organized these patterns into themes that ultimately summarized participant group behavior. Since RTA emphasizes the coder's reflection of the data over coding consensus we did not calculate inter-rater reliability, which aligns with the RTA methodology [13] and most qualitative research published in the HCI/CSCW communities [78].

Chapter 3

Findings

In our study, we observed a diverse range of participant behaviors and interactions with the robot that offered valuable insights into how they work alongside a robot teammate. The overarching patterns are: othering of the robot, workarounds for managing robot capabilities, role emergence, and robot intent and explainability. We discuss each of these in further detail below.

3.1 Othering of the Robot

Othering is the process by which individuals or groups define themselves as part of an in-group and perceive others as part of an out-group. This distinction is often created by highlighting desirable characteristics within the in-group while attributing undesirable characteristics to the out-group, thereby reinforcing social boundaries and distinctions between the two groups [14]. We observed participants othering the robot due to negative perceptions about the robot. This resulted in attempts to manage robot errors and ignore its contributions.

3.1.1 Negative Perceptions About the Robot

We observed that many groups had negative perceptions of the robot, which were expressed through both verbal and nonverbal behaviors.

For example, Group 3 commented out loud, *"Oh my god"*, or expressed nonverbal behaviors like laughter and sneering in response to the robot's movements. When Stretch

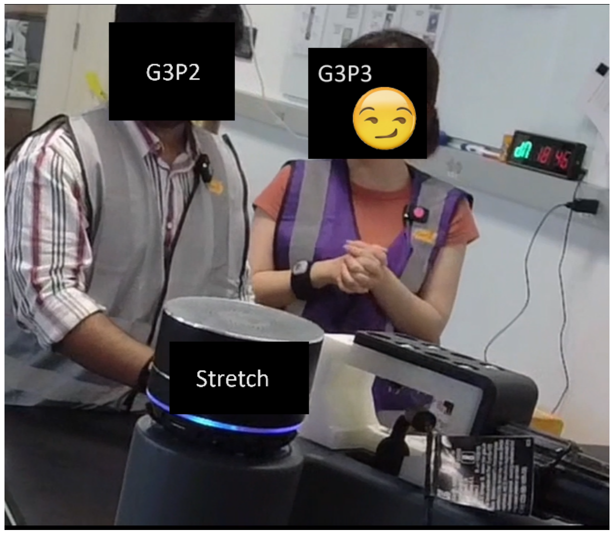

Figure 3.1. G3P3 displays othering behavior towards the robot by expressing mocking laughter in response to Stretch's slow and imprecise movements while picking up a block.

responded to a participant's request with "*I can help with that*," G3P3 reacted in an exasperated manner ("*Oh gosh*"), whereas G3P1 doubted Stretch's ability to do the task ("*Can he?*").

Similarly, we observed that Stretch's imprecise and slow behavior in retrieving the block resulted in Group 3 demonstrating othering behavior towards it. When Stretch claimed, *"I found something,"* and approached the object slowly before actually picking it up, G3P3 snickered and exchanged amused, incredulous glances with G3P2 (Fig. 3.1). This behavior demonstrates othering as it involves participants ridiculing the robot's perceived inadequacies, such as its imprecise movements and delayed responses, thereby reinforcing the difference between the robot and the human team members.

This was immediately followed by all three members simultaneously providing corrective instructions to the robot about its movement. Even though the team could have engaged in other tasks while Stretch proceeded to pick up 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 combination of P3's shared reaction to the robot and the team's micromanaging of the robot reveals their distrust of the robot's capabilities. It also reveals their belief that Stretch

Figure 3.2. Group 4 expresses othering behavior by huddling together, apart from the robot, and discussing their preference for robot behaviors.

required their instructions to achieve the pick-up task successfully.

In another instance, members of Group 4 used phrases such as *"Hey, buddy"* to refer to the robot, which suggests infantilization. This behavior not only undermines the perceived status and capabilities of the robot within the team but also reinforces a sense of otherness by emphasizing a perceived inferiority compared to human team members.

At another time when the robot offered its help after recovering from a technical failure, G4P3 responded with *"just sit there and look pretty."* G4P3's response elicited laughter from the other participants. This demonstrates the team mocking the robot's ability to contribute and its lack of importance to the team. It also suggested condescending and ostracizing behavior towards the robot.

Similarly, along the course of the task, the team gathered together to observe the robot as it attempted to pick up an object the team needed. While standing together as a group, all team members gazed at the robot as they discussed if they preferred the proactive robot over the passive robot. This exclusion of the robot was also demonstrated by non-verbal behaviors which included pointing at the robot as they discussed its behavior and laughing together. The team's behavior suggests that they regarded the robot as an out-group member.

3.1.2 Error Management

We observed that teams were more accommodating of their human teammate's mistakes than they were of the robot's mistakes.

For example, when G4P3 accidentally picked something up before they should have, G4P3's team members did not engage in accusatory behavior, and the team laughed about it.

However, when the robot took time to fetch objects and asked the team if they had found anything, G4P2 responded with *"Yes! We are just waiting on you!"* This response shows frustration with the robot's ability to support the team and describes the robot as the team's bottleneck or limiting factor.

In addition, when the robot made movements that were confusing for the team, they were misinterpreted by team members as the robot struggling to complete its task. For example, when the robot adjusted its movement to retrieve an object, G5P2 interpreted it as the robot struggling and began issuing low-level commands like *"Hey Stretch, can you go back?"*

3.1.3 Ignoring the Robot

Teams also treated the robot differently in terms of how willingly they interacted with it compared to human team members.

In Group 4, as team members searched for missing items, G4P3 wanted to confirm that Stretch had decoded the items in areas only accessible to the robot. They asked: *"Hey Stretch, did you scan this one over here,"* pointing to an encoded item. However, G4P3 repeated the question to G4P2 when they walked closer and did not wait for the robot's answer. When Stretch confirmed that it had scanned the item they responded with *"Yeah, Ok!"* followed by a snicker.

Furthermore, when strategizing to complete a task, the teams did not always integrate the robot into their plan. This suggests that they may not have considered the robot to be an integral member of the team.

For example, one task required Group 5 to find four boxes, which was explicitly stated in the clue's instructions. One of these boxes was kept in a region that was only accessible to the robot. However, the team chose to complete this task with just the three boxes they found in the regions accessible to the human teammates. This displayed a lack of willingness to engage with the robot, even when it would have made the task easier.

While teams displayed limited interest in interacting with the passive robot, we also observed that teams ignored the suggestions provided by the proactive robot. For example, team members in Group 3 actively ignored the robot in favor of their strategy for task prioritization. As the team collectively gathered to figure out their next steps, the proactive robot supported task progression by guiding the team members toward an item that the team needed but had not yet found. However, the team completely ignored the robot's suggestion to explore the area it had located the item in and instead asked the robot to fetch a different item.

This lack of willingness to interact with and include the robot as well as actively ignoring helpful robot suggestions further exemplifies the othering of the robot, regardless of condition.

3.2 Workarounds to Interact With the Robot

Teams came up with creative workarounds to interact effectively with the robot. This included modifying their prompts, requests, and strategies to better suit their perceptions of the robot's capabilities.

3.2.1 Using Simplified Language to Match Robot Capabilities

G4P3 simplified their prompts to the robot so that the robot could respond with a yes or no 3.3. For example, G4P3 identified a region of space physically, using co-speech gestures [46]. Then, they asked the robot to confirm if it detected any items they needed in that region. This suggests that the team perceived the robot to be incapable of engaging in human-like conversation, and adapted their language to suit the perceived linguistic capabilities of the robot.

Participants therefore modified their actions and instructions to circumvent the perceived restricted capabilities of the robot.

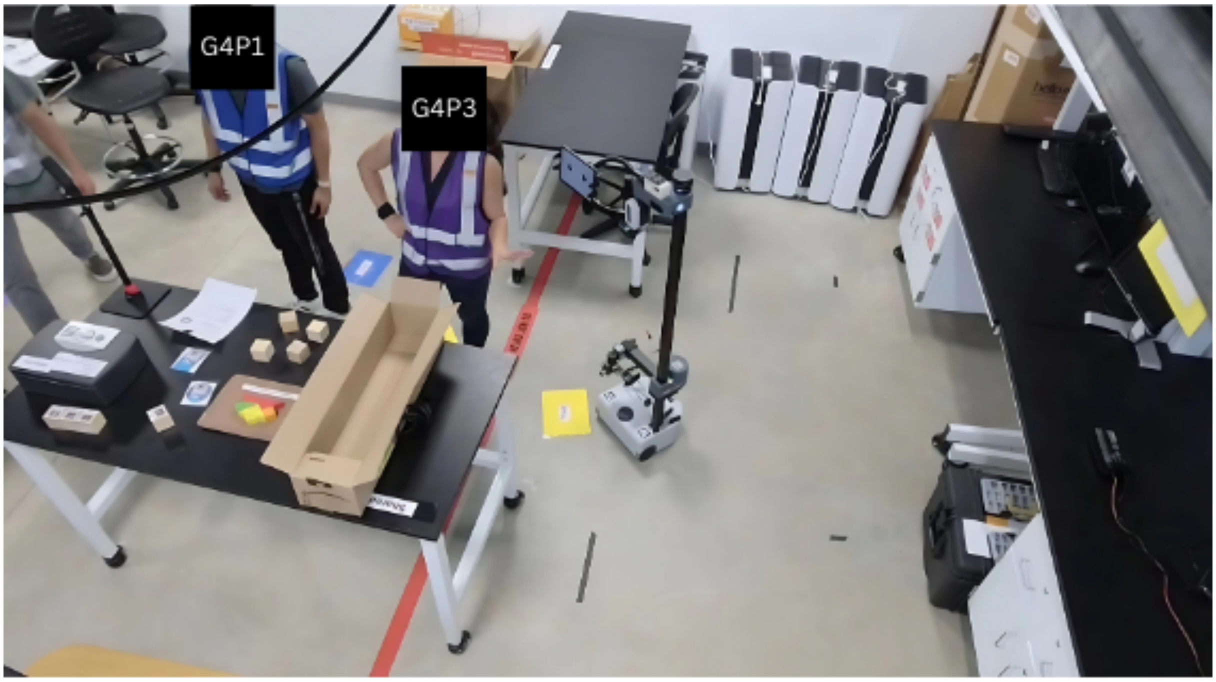

Figure 3.3. G4P3 simplified their prompts to the robot so that it could respond with yes or no.

3.2.2 Adapting Tasks to Robot Capabilities

If the team perceived that the robot may not be able to successfully complete a task, they modified their request to the robot to better match what they thought it was capable of.

In Group 1, the robot experienced a technical malfunction in its gripper just as it was about to hand over an object to a teammate. As a result of the malfunction, the robot was unable to open its gripper and complete the handover.

The robot clarified: *"I am sorry, but I am having some technical issues right now. Please give me a moment to recover,"* and *"Sorry, I need some help. Can you please take this from me?"* However, participants in Group 1 were reluctant to take the object from the robot until the robot released the object from its gripper 3.4. Therefore, when the robot did not open its gripper, G1P3 tried to simplify the handover task by asking: *"Hey Stretch, could you keep it on this table?"*

This depicted a scenario in which the participants tried to think of alternate tasks to assign to the robot that were perceived to be easier for it to complete but would still accomplish the team's goal.

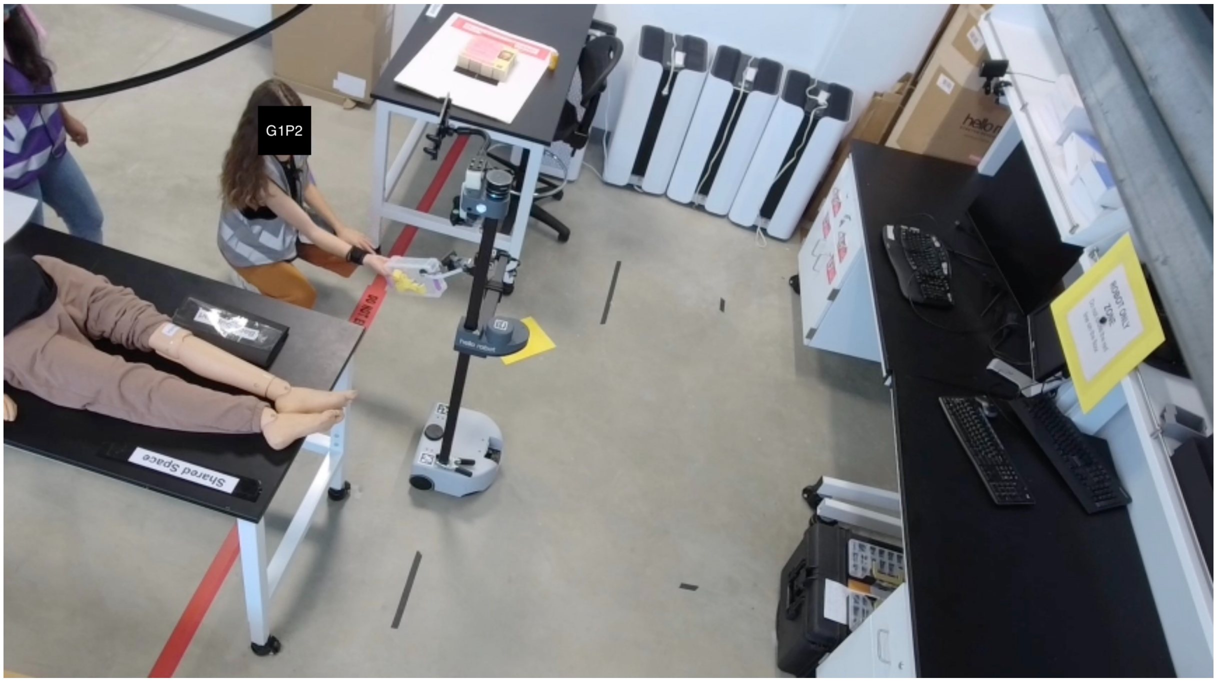

Figure 3.4. The robot experiences a hardware issue that prevents it from immediately handing over the object. G1P2 patiently waits for the robot to open its gripper.

In addition, when G4P3 sought the robot's help to locate the missing item, they assumed that the robot was unable to distinguish between found and missing items. They supported the robot by covering items that could "confuse" the robot.

In Group 2, the robot encountered difficulty during an attempted handover, causing the item to become wedged against a chair 3.5. The slow speed of the robot's movements exacerbated this issue and caused G2P2 to proactively intervene by extending their reach to meet the robot halfway in completing the task. In this scenario, the team resorted to a workaround solution: instead of waiting for the robot to attempt the handover again, G2P2 leaned in and grabbed the block, so that the robot only needed to release the object for the handover to be completed.

3.2.3 Accounting for Robot Speed

Participants also adapted their strategies to account for the time it would take the robot to complete different tasks.

For example, G5P1 planned the next steps of the task and incorporated robot slowness

Figure 3.5. When the robot is retrieving the item, G2P2 reaches over to take the item that is stuck. This is an example of how participants modified their actions to workaround the robot.

into the plan for future robot instructions: *"Whenever he [the robot] is done with that, ask him as soon as possible [to do the next task]."* This demonstrated the capability of human teammates to adapt to robot limitations while strategizing to improve their task efficiency.

3.3 Role Emergence

As the teams interacted with each other and the robot through the two escape room tasks, we saw the emergence of specific roles that participants either actively took on during the task or assigned to other team members. The main roles that emerged are robot mediator, robot manager, and group leader.

3.3.1 Robot Mediator

We observed instances where participants acted as mediators when communicating with the robot. For example, Group 2 was interacting with Stretch to get it to scan blocks with QR codes to reveal numbers. G2P1 showed the blocks to Stretch, whereas G2P2 had taken on the role of using those numbers to unlock the spill kit. When Stretch read out the number for the QR code (*"That reads 6"*), G2P1 repeated the number (*"Six"*) out loud while turning towards G2P2, so that G2P2 could enter the number on the lock. This was an interesting behavior since the whole team was gathered near Stretch, and Stretch was loud enough for all the members including G2P2 to hear what it said.

People generally engage in repetition as a way to acknowledge or confirm what was said by the other person [19]. However, in this scenario, G2P1's behavior demonstrates directed attention at G2P2 with the specific need to support G2P2 in their effort rather than acknowledge the robot.

3.3.2 Robot Manager

We observed that in a few teams, members either assumed or assigned the role of a robot manager, e.g., someone who is in charge of requesting the robot to do specific tasks [102]. This role was observed regardless of whether participants interacted with the passive or proactive robot.

For example, we observed this in Group 4 as they interacted with the proactive robot. Once the team determined that they needed to find blocks for the task, G4P1 immediately began to instruct the robot to grab a block. At the same time, Stretch proactively suggested that it could also help search for items. G4P1 acknowledged this, *"Perfect"*, but still felt the need to take on the responsibility of playing the robot manager and continued their request to the robot to grab the block.

We also observed an instance of a participant explicitly being assigned the role of a robot manager. G5P1 first suggested that G5P2 ask Stretch to fetch a vial once it had completed bringing the block to the table. Once Stretch brought back the block to the table, G5P1 addressed the team in general asking if they wanted to ask Stretch to get the medical vial (*"Do you want to ask him to go get the other one?"*). G5P2 responded to this request with *"Yeah"* and proceeded to request the robot to pick up the bottle on the table.

In both of G5P1's requests, G5P1 chose to assign the task of interacting with the robot to the other team members rather than directly asking the robot themselves. This demonstrates that G5P1 assumed the role of a task director who assigns roles and delegated the role of robot manager to one of the other team members. It is interesting as it suggests that the effort of managing the robot necessitates a separate role altogether. They pursued this option instead of picking the more time-efficient option of directly interacting with the robot themselves.

3.3.3 Leadership

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), directed the flow of the task, and updated the team about task steps and status.

In one scenario, after reading the clue, G5P1 assumed on behalf of the team that they only needed to find four blocks. However, this assumption was incorrect because they were unaware that only four of eight total blocks were valid.

G5P3 confirmed that they had indeed found all the blocks without any hesitation. This scenario illustrates G5P1's leadership role as both G5P2 and G5P3 deferred to G5P1's assumption without questioning or verifying it, despite it being incorrect. Their willingness to accept G5P1's statement without verification suggests a level of reliance on G5P1's judgment.

After hearing this interaction, Stretch offered to help search for items (*"Maybe I can help? I will also search for the items."*) G5P1 explicitly refused this offer and asked Stretch to come closer to the team (*"Uh no, Stretch, come here."*) This suggests that since they had already found the four blocks, G5P1 determined on behalf of the team that they were ready to move on to the next task.

G5P1 set their team up for progress on the next task by handing each team member a spill sock. They then directed the next step for the team to do as a whole: "*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. G5P2 and G5P3 did not verbally respond to G5P1, however, they both moved towards G5P1, indicating their acceptance of G5P1's leadership. 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.

G5P1 demonstrated their leadership in many ways in this situation. For example, they took the initiative to read the clue out loud to determine the steps to perform for the task. G5P1 also made assumptions on behalf of the team after reading the clue, and G5P2 and G5P3 supported this assumption through confirmations and agreements. G5P1's leadership influenced Stretch's actions as well. They refused Stretch's proactive offers to perform certain actions, and instead provided instructions that aligned with the team's current goals.

A leader emerged in Group 3 as well. 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.

3.4 Robot Intent and Explainability

Participant behavioral data also revealed that participants often struggled to understand the robot's intent and its capabilities. Our analysis suggested that participant's expectations of the robot were set by both verbal and nonverbal behaviors of the robot, including the motion of the camera and effectors.

3.4.1 Misleading Verbal Behavior

Participants were shocked when the robot expressed its limitations with tasks that they incorrectly assumed it could perform. For example, when G3P2 asked, *"Hey Stretch, scan this QR code,"* the barcode turned out to be invalid. In response, the robot informed them that it was unable to help. This surprised G3P3 who then responded with, *"What?!"*, and tried to reinforce their instructions to Stretch by saying, *"Read the barcode."* This indicated their disbelief that the robot was incapable of decrypting a barcode. The participants' surprise is understandable as the robot had previously announced that it could help read the barcodes. However, in this instance, it did not have the capability to explain that the current block G3P2 was holding was invalid, or why it could scan other barcodes but not this one.

3.4.2 Expectations Arising From Robot Embodiment

Furthermore, teams understood the robot's physical capabilities through its embodiment e.g., if a robot has a gripper then it should be able to grasp objects. Thus, the teams expressed surprise when the robot expressed its limitations in interacting with certain objects. For example, participants in Group 3 and Group 4 were shocked when the robot communicated that it could not grasp a vial.

This suggests that participants perceived the robot's capabilities simplistically and found it challenging to distinguish between the levels of effort required when interacting with objects of different shapes, textures, and weights.

3.4.3 Directional and Social Cues

The robot's body motion was also used by team members to clarify the robot's intent and generate directional cues. For example, G4P3 asked *"Hey Stretch, look at me"* indicating that participants considered face-to-face interaction with the robot to represent the robot's attention to the participants.

Similarly, G4P3 asked *"Hey Stretch, can you face where the safety box is?"* and wanted to use the robot's physical orientation as a way to "point" toward the items of interest.

Furthermore, the lack of directional cues and clarity regarding the robot's focus of attention also confused participants. While the robot was scanning an item placed on the cabinet, G5P2 asked it to scan an item they were holding in their hand. Consequently, when the robot announced the number of items scanned, G5P2 had difficulty determining which item had been scanned. If the robot was designed differently to better convey social information via its embodiment, movement, and gaze cues, that may have helped participants avoid this confusion.

This was further exemplified by participants' confusion regarding the robot's listening behavior. If a participant initiated a request, they expected the robot to display some cue to represent it was listening. For example, G5P2 kept repeating *"Hey, Stretch"* waiting for some response or cue from the robot. G5P1 then clarified *"I think once you say 'Hey, Stretch' it just listens, right?"* This suggests that individuals may need appropriate social cues or backchanneling to represent the robot's listening state.

Similarly, G1P2 interpreted a delay of 3 seconds in the robot's response to their request as a technical failure. This suggests that participants expected immediate feedback from the robot with either an appropriate response, an acknowledgment of the request made, or a social cue. They therefore interpreted an absence of feedback as an error.

Chapter 4

Discussion

Our results reveal that there are many factors that need to be better understood in order to integrate robots as effective teammates in human-robot action teams. These factors include error tolerance in high-stakes environments, managing expectations arising from the robot's physical embodiment, individual adaptation to robot capabilities, role emergence, and mitigating outgroup perception through robot social skills.

4.1 Error Tolerance in High Stakes Environments

In our study, certain robot behaviors such as the robot's speed and its position adjustment when interacting with objects were perceived as errors and robot ineffectiveness. This was because the robot performed the task in a way that was different from what participants expected.

This often resulted in people becoming frustrated or more closely supervising the robot. It is possible that people were less tolerant of the robot's perceived inefficiencies because they were accomplishing tasks in a timed manner and the team's success was at stake. In high-stakes environments, such as emergency departments and firefighting scenarios, where there are time constraints and high urgency of tasks, the tolerance for robot errors may be further reduced due to the dire consequences of failure.

While some studies have highlighted the perception of robots as essential team members in contexts like the military and bomb defusing, these dynamics were not explored in the context of perceived robot errors [109]. This raises questions about how perceived robot errors would affect human-robot relationships, and the robot's membership in the team in a high-stakes environment.

Framing robot expectations in advance can also help improve human perceptions of the robot [127]. The robot can set expectations about its performance for a certain task in real time to prepare people for what the robot's actions and behaviors may be like. For example, if the robot prefaces its actions with a statement like, *"Small objects are difficult for me to pick up, so I may need to move slowly or adjust my position to fetch the object,"* it sets clear expectations. Then, participants would understand that the robot is being cautious rather than failing.

Similarly, another study [131] indicated that an emotional apology positively affected more participants than no response, a standard apology about poor performance, or an explanation. Furthermore, this study identified emotional apology as the most effective method for time-sensitive scenarios. In the escape room, although the robot did not make any actual errors, the slowness could be perceived as an error especially since the tasks were timed. It is possible that an emotional apology could improve participants' perceptions of the robot and its limitations even though the robot may not be able to change its maximum speed due to safety constraints.

Thus, expectation framing and repair strategies such as emotional apologies might allow participants to be more tolerant of the perceived ineffectiveness of the robot.

4.2 Managing Expectations Arising from the Robot's Physical Embodiment

Our analysis suggested that participant expectations and perceptions of the robot were set by not just verbal behaviors, but also non-verbal behaviors and embodiment of the robot. This included the motion of certain robot sensors and effectors. However, the physical embodiment can also lead to confusion about the robot's capabilities. This explains why participants were shocked when the robot said that it could not pick up an object, as this was a violation of the participants' expectations.

On the other hand, if the robot did not have a gripper at all and said that it could not pick up an object, participants would most likely see the obvious limitation and not be surprised by it. For example, Stretch had a gripper that it used during the study to fetch different items. The participants interacting with the robot might assume that the robot can pick up most objects using the gripper. However, the design of the robot's manipulator (e.g., arm, wrist, gripper) may impose certain limitations on the robot's ability to interact with certain objects. Factors such as the shape, size, texture, and weight of an object would influence the ability of the robot to pick up the object. These limitations may not be easy to perceive from the physical embodiment of the robot alone.

Similarly, the camera and face-to-face interaction supported intentionality. When G4P3 asked Stretch, *"look at me,"* the robot rotated so that the tablet (which displayed the face) was directly facing them. G4P3 gave the robot further instructions only after it had completed its movement. This spatial orientation and face-to-face communication were associated with attention and listening. In addition, participants tried to figure out which items were being scanned by looking at the direction of the camera but were still unsure. Therefore if the robot has multiple cameras this intentionality can become vague. This suggests that there is a need to consider how different sensors may indirectly communicate intentionality or lead to confusion.

This demonstrates that physical embodiments alone do not convey sufficient information and can lead to violation of expectations.

4.2.1 Need For Explainability

In the study, if the robot was unable to support the team it simply responded with *"I am sorry, I am unable to help with that."* It did not provide any explanation as to why. For example, it could clarify if the object was too small to be easily picked up or if the location of the object was difficult to navigate to. This may have left the participants to wonder why the robot was refusing to help especially when it seemed capable of it.

One way to manage participants' expectations of the robot would be to have the robot provide more explanations about its capabilities and limitations (e.g., the task might not be necessary, the task is too difficult). Studies have found that robots should give sufficient explanations of their behaviors and failures, and provide concise summaries [45,72].

It would be worth exploring creative ways for a robot to generate interactional cues to convey intent, direction, and communication of ability or inability to improve participants' understanding of its functionality.

4.3 Adaptation

During the escape rooms, we observed that people started adapting to the robot's capabilities. People found alternative ways to interact with the robot, including simplifying instructions. In particular, they used the robot's physical embodiment and adapted their instructions to the robot's perceived limitations to accomplish the necessary tasks.

For example, G4P3 first asks the robot if it knows where another item is. However, they are confused when the robot asks that they look in the direction of its camera. G4P3 clarifies, *"are there any [items] on this side of the room that you see,"* indicating the area with arm movement. They further ask, *"are there any [items] underneath something?"* This raises questions about how physical embodiments such as a robot's sensors, chassis, or effectors should be positioned to clearly express attention and direction.

Although participants were able to navigate the limitations of the robot's behavior, the necessity for these workarounds indicates a breakdown in interaction. If the robot can provide relevant explanations and display cues, people can adapt their mental models of the robot and their subsequent interaction with the robot leading to more fluent interactions.

In an ideal scenario, a robot's behavior is explicit and communicative. However, interactions are dynamic, and improving them would require the robot to learn from human preferences and participants' understanding of the robot's capabilities. Specifically, observing a human's workarounds to the robot could unveil hidden human preferences and also guide the design of robot explanations.

4.3.1 Role Emergence

Distinct roles such as that of a mediator or manager emerged due to team members needing to support each other.

For example, the role of the robot mediator may arise from a lack of trust or reliance on the robot, prompting team members to support each other when the robot's responses are insufficient. Additionally, the role of the manager emerged as a necessity for managing perceived errors and navigating around the limitations of the robot, highlighting the importance of adaptive strategies in maintaining team efficiency and cohesion.

Improving the robot's capabilities to reduce the need for these roles can enhance overall team efficiency and effectiveness. However, certain roles may naturally emerge in human-robot interactions, especially in complex or high-stakes environments. Therefore, it may be beneficial to anticipate these roles and design systems that support and complement them.

Furthermore, the emergence of leaders in human-robot teams parallels a natural outcome in human-human groups as well, as there is a need for organizational structures to facilitate smooth collaboration. One study found that effective leadership of diverse teams requires proactive as well as reactive attention to teams' needs and adequate management of these processes through task- and person-focused leadership [50]. Since the escape room was a time-constrained task, the leaders that emerged tried to establish clear team communication, task coordination, and strategy to achieve team goals. They also considered what the robot should be doing and when based on task needs and perceived robot capabilities.

Such role emergence in human-robot action teams seems to arise in response to the team's perceived capabilities of the robot and the resulting need for greater human intervention and coordination.

4.3.2 Mitigating Outgroup Perception

In our study, we consistently observed othering of the robot across the majority of teams in both conditions.

We anticipated that the robot might be treated as an outgroup member because prior work suggests that having a robot on the work team can have a negative impact on in-group identification [95,101]. In our study, we tried to mitigate this effect by encouraging task interdependence between participants and the robot (certain tasks required abilities that only the robot had). Before the start of the escape rooms, we also emphasized to participants that the robot should be treated as another member of the team.

Despite these efforts to promote ingroup behavior and emphasize the robot's inclusion as a team member, participants still exhibited outgroup perceptions towards the robot. This indicates that additional factors may have influenced their perceptions such as their interaction experience or stronger reliance on human teammates than the robot.

4.3.3 Need for Social Skills

Due to our Wizard of Oz protocol, the robot's dialogue was strictly constrained to functional communication (e.g., "Yes, I can help with that", "Maybe I can help? I will also search for the items.") and general responses (e.g., "Yes," "No," "Yes, I agree"). The robot's behavior did not include any nonverbal social cues such as head movement, gaze direction, or turn-taking. The robot's lack of social skills may have contributed to negative perceptions of errors and slowness in dynamic situations.

This indicates that even among highly task-focused teams, there remains a necessity for some degree of social skills to mitigate negative perceptions of the robot.

By incorporating more social cues and signals, such as affective speech and non-verbal cues, robots have the potential to mitigate negative perceptions and enhance their integration within highly functioning teams. This is in line with previous work which has shown that social signals can improve human-robot interactions [3,85,90,113].

One study suggests that robots expressing group-based emotions based on team outcomes, rather than individual outcomes, were better liked and trusted by team members [111]. This highlights the role of emotional expression in fostering positive human-robot interactions as well as robot acceptance.

Other work has found that a robot's gaze [22], statements of team appreciation [130], encouraging speech [114], and positive attitude [29] all play a role in improving the robot's acceptance. At the end of the escape room, when G4P3 asks Stretch if it can high-five, Stretch responds, *"I'm sorry, I am unable to help with that."* G4P3's affectionate *"aww"* suggests they found the robot's response endearing. This indicates that participants would have interacted with the robot as a social agent if given the opportunity. Dialogue that expresses appreciation of team members such as "Great job, team!" could help robot acceptance.

This is especially important for the social integration of a robot as a team member. However, this must be designed carefully, as action teams work in high-stakes professional environments where humor may not always be welcomed at all times.

4.4 Implications for HRI

The purpose of this study was to explore these two questions: 1) How do action team characteristics affect how team members interact with and respond to a robot?, and 2) How do a robot's actions influence intra-team dynamics? To this end, we studied how participants collaborated with a robot to complete two escape rooms. Our findings have several implications for the HRI community.

Firstly, we emphasize the importance of considering both the functional and social aspects of a robot's role in fostering acceptance within human-robot teams. These social skills include verbal and nonverbal communication, such as positive speech, to express team encouragement, as well as nodding or eye contact for active engagement. Future work could include exploring how these social skills (speech and nonverbal cues) can be implemented to support the addition and inclusion of a robot as a social agent.

Secondly, our work highlights adaptive behaviors exhibited by participants in action teams to accommodate the robot's capabilities or perceived limitations. Some of these behaviors included the emergence of different roles. Therefore, robots may need to understand the roles of different team members to effectively support them. By recognizing and responding to the diverse roles within a team, robots can enhance collaboration and productivity in various collaborative settings. One question worth exploring is how a robot could do this autonomously, especially when taking into account the nuanced dynamics of human-robot collaboration in high-stakes environments.

Additionally, the limited interaction time between participants and the robot in our study may not have allowed participants to bond with the robot enough to be more tolerant of the robot's limitations. Although the overall study length was quite long, the limited interaction time can be remedied by conducting a single study session of longer length rather than two 20-minute sessions. This allows for uninterrupted time for the participants to bond with the robot.

Furthermore, while our study focuses on the role of the robot within teams, it is essential to acknowledge the significance of human-human interactions. The ad hoc nature of team formation in our experiments may have influenced the dynamics observed, warranting further examination of how team composition affects collaboration. Understanding the process of group formation and maintenance, as well as its evolution over the course of the tasks and across the rooms, would provide valuable insights for reflecting on the robot's influence within the team.

Lastly, we explore the impact of a robot's physical embodiment on shaping users' expectations of its capabilities. This includes how a robot's camera, arm, or even base movement can influence teammates' perceptions of its functionality and competence within collaborative tasks. Understanding these aspects provides insights into designing robots that not only meet functional requirements but also align with users' social expectations.

It is important for the HRI community to consider these findings to better design the robots to facilitate seamless integration within human teams in various real-world settings.

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