Taking Initiative in Human-Robot Action Teams: How Proactive Robot Behaviors Affect Teamwork

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ABSTRACT

People coordinate in action teams to accomplish shared goals in safety- and time-critical contexts such as healthcare and firefighting. Operational failures in these teams can cost lives. Therefore, in our work, we explore how robots that take initiative to support team and task success can augment action teams. We designed and studied proactive robot behaviors in non-dyadic (three humans and a robot) action teams to better understand factors that support the acceptance and effectiveness of proactive robots. Our work will support better human-robot teaming in action teams by addressing gaps in how robot initiative impacts team dynamics, preferences for proactive robot behaviors, and how proactive robots can take initiative based on task states to empower their teammates.

CCS CONCEPTS

• **Human-centered computing → Interaction design**; • **Computer systems organization → Robotics**.

KEYWORDS

Human-Robot Teaming, Groups and Teams, Proactive Robots, Group Dynamics

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1 INTRODUCTION

Collaborating in teams is an essential aspect of our species. We farm for food, play sports for entertainment and competition, and build bridges and cities to improve the quality of our lives. All these require us to coordinate with one another in a fluent, cohesive, and proactive manner.

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Figure 1: Our work aims to support action teams by designing proactive robots that can take initiative to advance team goals. We explore this within the context of escape rooms using Stretch, a mobile manipulator robot. *From left to right:* Stretch interacts with participants during an icebreaker, participants solve a puzzle and the robot hands over an item they need, Stretch reminds users about safety considerations while administering first aid.

One type of team that is of interest is an action team. In action teams, members perform in fast-paced, unpredictable situations and use their specialized skills to improvise and coordinate their actions [13]. For example, emergency medical teams are action teams.

Robots have the potential to augment action teams by taking on redundant and/or unsafe tasks allowing people to focus on tasks that require their specialized skills. However, given the time- and safety-critical nature of these teams, failure can be costly, possibly leading to massive financial losses, grave harm, or death. Therefore, robots must be well contextualized to the needs of the team, and their tasks to be helpful.

Robots in action teams should be able to work fluently to support task progression and safety. This is because robots can affect team dynamics such as increasing intrateam communication [41, 42], regulating conflict [23], and furthering trust-related behavior [43].

One robot behavior that is of interest is *proactivity*. Proactive robots anticipate team needs and take initiative to support teamwork. For example, Baragalia et. al. [4, 5] have shown that people prefer to interact with robots that exhibit proactive behaviors and consider them to be better teammates.

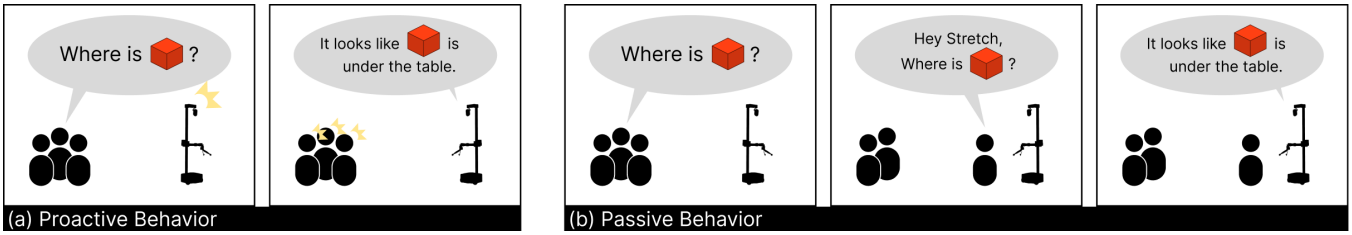

Figure 2: Examples of behaviors from the proactive and passive robot conditions. (a): The proactive robot notices the team is stuck, and takes initiative to assist its teammates. (b): The passive robot waits for a human-request before assisting the team.

However, prior work has primarily focused on dyadic human-robot interactions or studied proactive speech and proactive interactions independently. In the context of action teams, this is problematic as these teams likely consist of multiple team members, and their shared understanding is impacted by both behavior and dialogue.

Our work aims to design proactive robots that are effective in action teams.

Through our research, we consider 1) how teams perceive different levels of robot proactivity, 2) what factors guide their preferences, and 3) how these behaviors impact team dynamics. Therefore, our current research objectives include understanding: 1) factors that impact preferences for proactive robot behaviors in action teams, and 2) how robot proactivity affects team dynamics such as team cohesion, trust, and shared mental models.

Our research will support the understanding of team dynamics and develop new algorithms through which robots can make sense of the world and act to support their teammates.

2 RELATED WORK

Human-Robot Action Teams: Researchers have modeled robot behaviors on how humans collaborate to support human-robot teaming. Robots are able to identify human intent, anticipate the next steps for tasks, and adapt their actions accordingly [12, 18, 19, 26, 31, 37, 40]. They can also perform temporal adaptations during group synchronization tasks [21, 22]. Well-designed and contextualized robots can support action teams in acute care [16, 28, 44, 45].

Proactive Robots: Robot initiative can support humans with a diverse array of tasks ranging from performing activities of daily living [33, 34, 37] to simple assembly tasks [30]. Proactive robots are known to improve team performance and may reduce robot and user idle time [20, 29]. They are perceived better in terms of likability, performance, and team effectiveness [2, 5, 50]. Proactive dialogue is perceived as trustworthy and sympathetic [25].

However, human teammates may have negative perceptions of proactive robot behavior as well. For example, proactive robots may come across as interrupting and more controlling [35], and harder to use [14]. Additionally, they may add to a person's cognitive load and reduce situational awareness [50]. Therefore, further investigation is required before integrating proactive robots into action teams.

Escape Rooms: Escape room games have been used to study human-human [3, 9, 17, 49] and human-robot teaming [15, 47]. Escape rooms can be designed to simulate safety- and time-critical tasks that impose interdependence between team members. This makes them suitable for studying teaming.

3 METHODOLOGY

We conducted a 2 (escape room: medical vs. hazard) x 2 (robot behavior: proactive vs. passive) mixed methods within-subject study to understand human-robot teaming with proactive robots. We counterbalanced the conditions to reduce order and game effects. The study was conducted using a constrained Wizard of Oz (WoZ) [38] paradigm across the two robot conditions. In the passive condition, the robot only acted and communicated when a human teammate initiated an interaction or request. In the proactive condition, the Wizard followed a script that guided how the robot should take initiative to support team progress. These robot behaviors are presented in Fig.2.

Escape Room Design: We designed two escape rooms with different themes (medical and hazard) to mitigate learning effects. We designed the tasks to require similar effort to complete and mitigate the game design's influence on the results. We extensively piloted the design of both escape rooms to ensure that the escape room tasks: necessitated teamwork, were fun to complete, had human-robot interdependence, and could be completed in 20 minutes. In our study, 5 ad-hoc teams of 4 participants (3 people and a robot) completed two 20-minute escape rooms.

Robot Design: We used the Stretch robot to conduct the study (see Fig. 1). Stretch is a mobile manipulator able to move around, pick and place objects, and perform audio communication. We added a tablet to Stretch which displayed a blinking face to support natural interaction [1, 24]. We used Siri's gender-neutral voice [36] for Stretch to mitigate gendered perceptions of the robot. All verbal utterances for Stretch were pre-recorded to standardize interactions across teams.

Measures: We collected data using sensors, surveys, and interviews. In this report, we summarize the results of the interview data while our analysis of the other data is ongoing.

Sensors: We recorded the participant teams using 10 cameras for full room coverage. These cameras streamed wirelessly to an app on two tablets which the researchers used to track participants inside the room. Participants also wore wireless lapel microphones to record audio data and inertial measurement unit (IMU) sensors on their dominant hand to record activity data.

Surveys: Participants responded to surveys that included a manipulation check, the Negative Attitudes Towards Robots (NARS)[32],

(sub)scales on team dynamics: cohesion [27], trust [10] and shared mental models [46], and team's perceptions of the robot [39].

Group Interviews: Teams also participated in semi-structured group interviews where they shared their experiences of teaming with the robot. Three researchers independently coded the data and over several discussions generated themes from the data.

Procedure: Once participants arrived they were greeted by a researcher. After introductions, they took the NARS survey. Participants then put on unique colored vests and the sensors. After this, they were informed about the escape room rules and then they participated in the two escape room games. A survey and a group interview followed each escape room game. The entire study from arrival to conclusion took around 120 minutes.

Results and Discussion: We analyzed interview data using reflexive thematic analysis (RTA) [6, 7]. Results of our qualitative analysis of the group interviews revealed that teams differed in their preference for proactive and passive robot behaviors based on a number of factors. Teams that preferred the proactive robot considered the robot's perceived capabilities, independence, and helpfulness as guiding factors for their preference.

On the other hand, teams that preferred the passive robot considered control over the robot and the task, quality of robot communication, and perceived robot capabilities as factors that motivated their preference. All teams also anthropomorphized the robot, some teams wanted more naturalistic communication with the robot and trusted their human teammates over the robot.

Our results suggest that when the perceived cost to the team is high, people prefer to rely on each other rather than a robot, desire more control over the task and robot, and have a lower tolerance for when the robot makes a mistake. Even though participants desired more naturalistic communication with the robot, we must also consider how to align the desire for fluent robot speech with ethical considerations such as accuracy of information when using large language models (LLMs) [48]. Other ethical considerations include how to prevent proactive robot behavior from misleading people about its capabilities and knowledge, as well as consider worker displacement [8, 11] and the impact of proactive robots on reshaping workspaces for humans.

4 ONGOING AND FUTURE WORK

We are currently conducting a qualitative analysis of video and audio data to identify behavior patterns in action teams when interacting with passive and proactive robots. This will support our understanding of team dynamics and what makes a good human-robot action team.

We will analyze the survey data to further our understanding of how teams strategize and how robot behaviors affect team dynamics such as cohesion, trust, and shared mental models. In the future, we will use the collected sensor data (video, audio, and IMU) to build robots that are capable of understanding the world state and can generate actions they needs to take proactively.

We will also analyze the video and IMU data to develop activity detection models, then use these models that will be used to inform how we build future robot controllers. For example, robot controllers that allow robots to execute desired robot action based on the task context and team progress. We will evaluate our controllers on an autonomous robot in a similar experimental paradigm.

Our research contributes to an improved understanding of human-robot team dynamics in fast-paced, uncertain environments. This will lead to the design of research-informed robot behaviors that can positively influence team dynamics improving robot acceptance and team outcomes. Through our research, we aim to address the challenges of worker safety and robot effectiveness in dynamic environments.

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