TEAM COMMUNICATION IN PRE-MISSION BRIEFS AND EFFECTIVENESS IN DISTRIBUTED ACTION TEAMS

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Workplace research suggests that roughly equal communication between teammates is positively associated with team effectiveness. A distinction between teams in these studies and distributed action teams is the degree of role specialization and context-driven communication which may entail unequal degrees of communication. Yet, distributed action teams may have more equal footing to provide inputs in contexts such as mission planning or briefings. Twenty-two ad hoc teams participated in a simulated ground combat vehicle task in which teams conducted six-missions and briefed before each mission. We used team performance, team situation awareness, team workload, and team resilience as team effectiveness criteria. Balanced degrees of communication in mission briefs were correlated with performance and resilience measures, and largely uncorrelated with situation-awareness and workload measures. The overall amount of communication was also largely uncorrelated with all effectiveness measures. The results suggest that communication balance in mission briefs may help predict effectiveness in action teams.

INTRODUCTION

Many human–autonomy teams (HATs) may be classified as distributed action teams. Distributed action teams achieve mission objectives through a confluence of interactions with technologies and time-constrained coordination among specialized teammate roles (Sundstrom et al., 1990). Improving the effectiveness of these teams to achieve mission objectives is a key aim of future HAT systems such the U.S. Army's Next Generation Combat Vehicle (NGCV) systems (Lee, 2017). To improve effectiveness, autonomous agents need to integrate into complex and dynamic teamwork in addition to contributing their unique capabilities. But to assess future systems' effects on teamwork, valid measures of team effectiveness are needed.

Although team effectiveness is a unifying concept across HAT research, how team effectiveness is defined and measured varies widely (National Academy of Sciences, 2021). For instance, team effectiveness may be defined as achieving performance outcomes. Although this approach is straightforward, distributed action teams often have limited control over outcomes. Alternatively, effectiveness may be defined to include team factors that contribute to achieving performance outcomes. Examples of these factors include team situation awareness, team workload, and team resilience. In our efforts to develop metrics and models of team effectiveness, we focus on measuring these factors as dynamic team processes.

The overall aim of our project is to develop interaction-based measures that capture various aspects of team effectiveness in HATs. The quality of our measures depends on their validity as well as their applicability to the development of NGCVs. We believe that ideal measures of team effectiveness for application to NGCVs have common criteria: 1) they are unobtrusive, meaning their collection does not interfere with teams' activity; 2) the generation of these measures may be automated; 3) measures may be collected in real time; and 4) measures do not depend strongly on contextual knowledge or ground truth. At the current stage, these criteria are aspirational in practice, but they have driven us to focus primarily on communication flow measures (i.e., who is talking and when).

The current study focuses on the relationship between team communication flow during mission briefs and team effectiveness criteria. Workplace research has shown that communication flow balance between teammates may be a strong predictor of team effectiveness (Duhigg, 2016; Pentland, 2012). An important distinction between these more knowledge-oriented teams and action-oriented HATs is the degree of role specialization and context-driven communication inherent in team tasks. For example, we do not expect combat vehicle crews to all communicate equally in field operations, as some roles entail different levels of communication (e.g., a vehicle commander compared to a driver). Yet, mission briefings are a context in which individuals have more equal footing to provide inputs and collaborate for mission success.

Our research question was: *Is balanced communication in action-oriented team pre-mission briefs related to team effectiveness?* We conducted a study in which teams briefed and completed several missions in a simulated combat vehicle task. We hypothesized that balanced communication in briefs would be associated with team effectiveness during field operations.

METHODS

Participants

The data used in this study was obtained from 22 teams. Teams consisted of three participants (N = 66) recruited from a large southwestern university and three confederate researchers. Participants were either undergraduate or graduate students, ranging in age 18 to 34 (M=21.4, SD=3.2) with 19 women, 44 men, and three that did not report in total. Participants attended the experiment remotely from their personal devices. To participate, they were also required to have computer gaming experience, to have a computer that can run the testbed applications, and to be able to work in a quiet and uninterrupted environment. Participants were also required to be 18 years old, be fluent in English, and have normal (or corrected) hearing and vision.

Equipment and Materials

A virtual battlefield environment was built and customized in Minecraft Java Edition Version 1.12.2 and community-based Forge mods. A Minecraft Forge server hosted the Minecraft world as a multiplayer environment, and participants connect to the testbed's Minecraft clients using Parsec. Zoom was used to conduct the experiment over a web-conference call using voice- and text-chat, screen sharing, and recording features. Data in the virtual environment were recorded using OBS screen capture and Minecraft's logfile system. Survey measures were collected using Qualtrics. Lastly, training was administered via PowerPoint and hosted on Google Drive.

All three experimenters used a computer with Minecraft, Parsec, OBS, and Zoom to run the experiment. One experimenter computer was designated as the Minecraft Server host. Participants used their own personal computers, keyboard and mouse, and microphone setup.

Task Scenario

The task scenario is a series of ground combat vehicle reconnaissance missions in a simulated scenario set in Minecraft. Teams remotely operate Robotic Combat Vehicles (RCVs) to identify relevant objects in a battlefield environment and take appropriate actions such actions such as reporting intelligence, calling artillery, or requesting external support. The scenario is divided into six missions. Each mission contains instructions (e.g., map, relevant tasks, operating boundaries) which are discussed in a 3-minute brief prior to execution. In addition to basic tasks, teams may be provided special instructions that include specific coordination requirements (e.g., destroy all enemies before proceeding to a waypoint), additional requirements may be called in by confederates. The scenario also includes two major perturbations, which are unexpected events that require novel team coordination (major perturbations are described in Lematta et al., 2021b).

Team Composition

Teams in our scenario are HATs composed of five agents with 4 unique roles: 1) Two *RCV Operators* (two randomly assigned participants) control RCVs in the Minecraft world to find and report identified objects and their locations to the team; 2) Two *RCV Agents* (Wizard of Oz confederates) help their respective RCV Operators by detecting the presence of objects and automatically focusing the RCV's camera on a detected object on request; 3) a *Coordinator* (one randomly assigned participant) uses a map to track the location of objects in the environment and interacts with an external Commander to report the team's findings and request services (e.g., artillery and technical support) having no view of the Minecraft world; and 4) a *Commander* (one confederate) receives reports, fulfills accurate artillery requests, and requests for technical support. The team composition is shown in Figure 1.

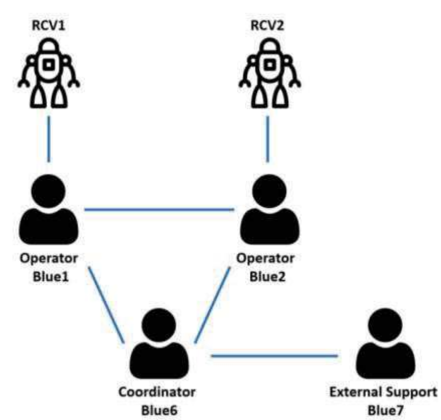

Figure 1. NGCV team composition.

Teams communicate primarily on a shared voice channel. Although the entire team may hear the Commander, the Commander may only hear inputs from the Coordinator. Additionally, the RCV Agents interact with RCV Operators through a text-chat system in Minecraft. Operators may request the RCV Agents zoom in on a previously detected object by pressing "1" for a potential target and "2" for an obstacle.

Procedures

Several procedures in this study were adopted to handle remote research specifically and are notable for that purpose. For a more detailed description of these procedures, see Lematta et al., (2021). Prior to attending an experiment session, participants attend a separate check-in session to verify they have all the required equipment and software. Once they have been checked-in, they may proceed to attend their scheduled experiment. After participants connect to the experiment session and provide consent, they are assigned to a unique ID number and a call-sign (e.g., Blue 1, Blue 6) corresponding to their team role. Experimenters confirm once again that their equipment and software meet the necessary requirements, particularly that they can control Minecraft via Parsec and that their microphone is clear. Then, training proceeds with individual role training. After role training, the Commander confederate guides the participants through a practice mission. Then, the team proceeds to start the missions.

A mission consists of a 3-minute brief segment and a 12-to-16-minute execution segment. In between each mission participants fill out a brief survey assessing high-level trust and workload constructs. Participants fill out a larger survey at the end of mission 3 and mission 6.

Measures

Communication. We measured the degree and balance of communication in all six mission briefs. *Degree* refers to the amount of talking (in seconds). Degree was measured for each teammate and totaled for an overall degree score. For communication balance, we calculated the *coefficient of variation* (CV) using the standard deviation and mean of each teammate's degree of communication:

$$CV = \frac{\sigma}{\mu}$$

CV reflects the dispersion of communication degree around the mean. Relatively higher values of CV mean higher imbalance in the amount of communication between teammates.

Team performance. Three dimensions of team performance were scored. These were the total amount of damage taken from enemies by each RCV, the accuracy of the Coordinator's map, and the time to complete a phase in minutes and seconds.

Team workload. Team workload was measured using a 3-item questionnaire. Participants rated their agreement with the following items on a Likert-scale from 1-7: "I had to work hard to accomplish my individual task", "A lot of teamwork was required", and "My team worked as efficiently as possible". These questions reflected taskwork, teamwork, and taskwork-teamwork balancing (reverse scored) dimensions respectively.

Team situation awareness. The Coordinated Awareness of Situation in Teams (CAST; Gorman et al., 2006) was used for communication flow in enemy target reports. We calculated signal detection measures (Stanislaw and Todorov, 1999) in enemy target reports based on the essential communication involved (Kim, 2021). This yielded four measures: hits (correct communications), false alarms (incorrect communications), misses (omitting necessary communication), correct rejections (omitting unnecessary communications), and the sensitivity measure d'. Then enemy target reports scored in total throughout the 6 missions.

Team resilience. We measured the flow and timing of responses to two major perturbations as team resilience measures. CAST was applied to communication in perturbations using the method described above, generating hit, false alarm, miss, correct rejection, and d' scores. For time-based measures, we used the overall time to resolve the perturbation from onset (i.e., relaxation time; Graham et al., 2021) as well as the time to coordinate perception and action (resolving excluded) in seconds (Hoffman and Hancock, 2017). Due to unequal timeframes of the two major perturbations, we used the Z-score for time-based resilience measures.

Analysis

The team communication and effectiveness measures were aggregated for the entire experiment. A bipartite correlation matrix was generated comparing communication degree and the between-teammate coefficient of variation for communication degree to team performance, workload, situation awareness, and resilience measures. In the following section, we report significant correlations.

RESULTS

Significant correlation results are summarized in Figure 2. For communication degree, there was a significant correlation with a team situation awareness measure hits on enemy target reports, r(22) = 0.503, p = 0.017. Teams that communicated more in mission briefs also had more correct communications in enemy target reports. All other correlations between communication degree and team effectiveness were not significant.

For the CV of communication degree, there was a significant correlation with two performance measures, damage taken, r(22) = 0.519, p = 0.013, and completion time, r(22) = 0.459, p = 0.032. Teams with more balanced communication in briefs took less damage and completed missions faster. There was also a significant correlation with the team workload measure of balancing taskwork and teamwork, r(22) = -0.444, p = 0.039. Teams with more balanced communication rated their team more efficient overall. Finally there were significant correlations between CV and three resilience measures: hits on perturbation communications, r(22) = -0.549, p = 0.008; false alarms, r(22) = -0.472, p = 0.026; and total relaxation time, r(22) = 0.615, p = 0.002. Teams with more balanced communication in briefs communicated more overall in perturbations and overcame perturbations faster. All other measures, including all team SA measures, were not significant. In sum, CV of communication degree was correlated with several performance-based and resilience-based measures and largely uncorrelated with team SA and team workload measures.

DISCUSSION

In this study, we were interested in the relationship between communication balance in mission briefs and team effectiveness. Team effectiveness encompasses multiple dimensions, and for this study we considered team performance, team situation awareness, team workload, and team resilience. We found that communication balance, measured as the CV of communication amounts between speakers, was correlated with several of our performance and resilience measures but largely uncorrelated with SA and workload measures. This supports the hypothesis that CV in mission briefs is potentially related to team effectiveness in our simulated combat vehicle task. However, the types of effectiveness criteria matter.

Many factors that may have contributed to communication imbalance in our teams, such as engagement, trust, and implied interaction structures. Many factors may also drive the relationship between balance in briefs and team effectiveness outcomes, such as plan quality and positive team dynamics. For example, in our major perturbations, teams benefitted from collaboration between Vehicle Operators, whereas enemy target reports generally did not require interaction between Operators. Although future studies should investigate these factors, our approach, by design, was not intended for a detailed analysis, such as what information was shared in briefs compared to task execution. Rather, this study's objective was to advance the CV measure toward our four criteria for team effectiveness measures: unobtrusive, automated, real-time, and context-independence. The CV measure was indeed collected unobtrusively and processed automatically, as it only requires data on who is talking and when, and future studies could apply this measure in real-time and in a predictive manner. Future work should also consider the generalizability of this measure to other contexts, in particular situations that do not impose strong constraints on communication distributions.

We used 18 measures of team effectiveness in this study, and we expect they are not all equally sensitive to

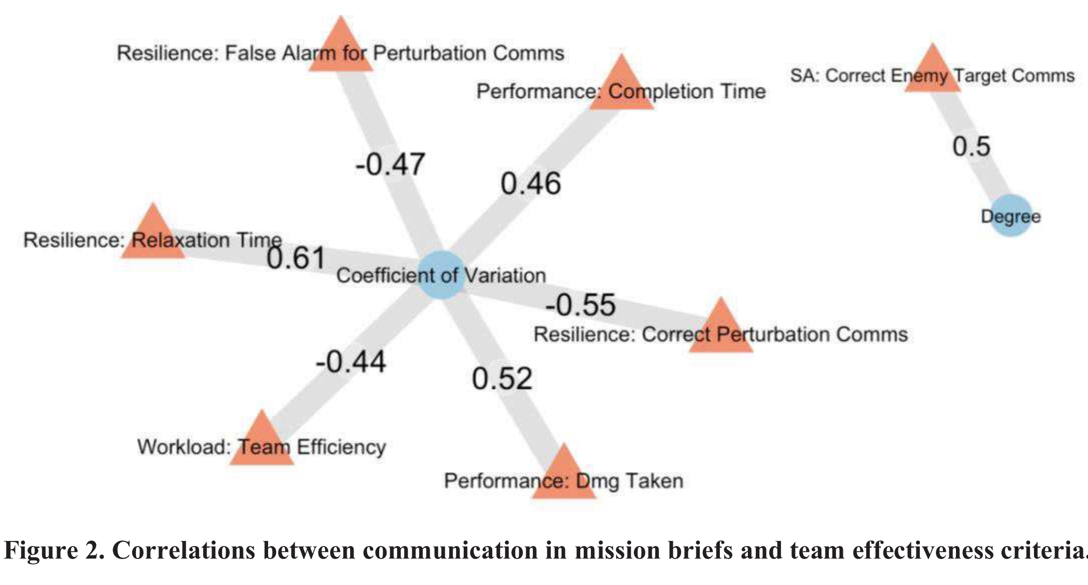

Figure 2. Correlations between communication in mission briefs and team effectiveness criteria.

capture their intended dimensions. We suspect our survey measure of team workload may have been insensitive to variations in team coordination and collaboration demands. Specifically, workload at the team-level may be sensitive to social factors, such that demands to collaborate (i.e., in our perturbations) may stress teams differently depending on how well they work together. Future studies should consider how to assess workload at the team-level by incorporating factors that constrain working relationships like trust.

As more process-based measures of teamwork are accumulated, there is potential for more holistic representations of team effectiveness. Tools such as cluster analysis, multidimensional scaling, or Pathfinder networks can help make sense of effective team processes. For instance, some team processes may influence resilience more than workload, as this study suggests. Representations of team effectiveness may be used as critical indicators in dashboard-style applications to enhance system monitoring or used as inputs for AI/machine learning. For our initial purpose of improving team effectiveness in NGCVs, we consider feedback on team effectiveness to be critical for informing the development of future systems to be used by distributed action teams.

CONCLUSION

This initial exploration relating communication in mission briefs to team effectiveness is a starting point that needs further work. Future work should explore those relationships in finer detail to determine if specific variables of the mission or team context or specific team tasks or events drive those relationships. In a similar vein further research should explore how to maximize the benefits provided by communication distribution, based on the information shared during the briefing or mission. Work toward these goals is already scheduled into planned future studies.

ACKNOWLEDGMENTS

We thank our sponsor, the U.S. Army Research Laboratory, under the Cooperative Agreement No. W911-NF-18-2-0271. The views and conclusions in this document are those of the authors and should not be interpreted as representing the official policies, either expressed or implied, of the Army Research Laboratory or the U.S. government.

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