Team communication behaviors of the human-automation teaming

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Team Communication Behaviors of the Human-Automation Teaming

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***Abstract*— If synthetic teammates are to be considered "team players", then they must be better equipped to handle the subtleties of communication and coordination with their human teammates. In this study, the team communication behaviors of a human-automation team were analyzed for the identification of which are the best predictors of team performance. The LASSO (Least Absolute Shrinkage and Selection Operator) method was used to select the team communication behaviors that were the best predictors of team performance and, in the end, 16 such role related communication behaviors (at both the role and condition level) were included in the final model. Findings indicate that in general, negatively perceived communication behaviors are predictors of negative team performance. Through this study, we also learned that even when human team members follow their optimal and expected communication behaviors when communicating with a synthetic teammate, these behaviors are still predictors of negative team performance. This finding holds important future considerations: even if human team members are properly communicating with a synthetic teammate, the errors and lack of human-like behavior on the part of the latter can still result in a negative team performance.**

Keywords—communication behaviors, human-automation teaming, synthetic teammate, team coordination

I. INTRODUCTION

Teams are becoming more adaptable and flexible in how they are both defined and composed. Traditionally, a *team* has consisted of two or more *human* individuals working together on a shared goal or task [1]. Yet, in recent years, a team may consist of both *humans* and variations of *machines* working jointly together. The integration of both humans and machines working together has led to the advent of human automation teaming [2]. This new dynamic has changed the way that we currently view, investigate, and most importantly utilize teams in a work environment. Machine intelligence and advanced robotics have caused many technological innovations, particularly in the development of highly automated systems. These systems are now often a critical component of complex operational work environments (e.g., military command-and-control or emergency response), aiding humans in their tasks or sometimes even fulfilling the roles of human teammates.

Due to the perceived value of human-automation teaming, many scholars have directly focused on both conceptualizing and empirically testing human automation teaming in both synthetic and real world environments (e.g.,[2]–[4]). A human-automation team can be defined as, "*the dynamic interdependent coupling between one or more human operators and one or more automated systems requiring collaboration and coordination to achieve successful task completion*" [2:B64]. Through technological innovation, there are many recent cases that have demonstrated the power and advanced abilities of automation within teams. Typically, and traditionally, automation in human teaming has meant that an aspect of the team's work would be aided through automation. An example of this is the capability of auto-pilot in many aircrafts. Pilots routinely turn control of their aircraft to the auto-pilot in "cruise" phases and this aids the pilots' work [2]. Yet, although the auto-pilot function provides feedback and suggestions to human team members, the interaction lacks real-time, back-and-forth communication. In response to this more simplified perspective on human-automation teaming, Wijngaards and colleagues [5] went a step further by developing an "actor-agent community" [5:35] wherein the automated systems behaved like teammates by actively participating and giving orders to other human teammates.

This work and others [2]–[4] [6]–[7], represent the next step in developing more robust automation within human-automation teams. Future, and in many cases current automation needs to be more aware of their team members, the context of work, and the specific task that the team is working on. In general, the automation needs to have much of the functionality that real human team members have. Aspects of teamwork, such as communication, coordination, and awareness are critical to team effectiveness [8]. Historically, automation has lacked many of these features resulting in the automation being an aid that is dependent on the team members directing it [6]. Future automation capabilities should be able to adequately interact with real human team members in real time. Fortunately, in recent years, an influx of more adaptive and interactive automation capabilities has increased the benefits of human-automation teaming [4], [7], [9], [10].

With these new automation features and capabilities comes a whole new set of problems that must be empirically investigated. Specifically, very little is known about how communication and coordination with an automatized or

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synthetic teammate affects team level interactions [4]. The effects that these interactions have on team performance is also poorly understood [10].

In this study, we specifically focus on how a synthetic teammate communicates with human team members through a variety of verbal behaviors. The synthetic and human teammate's effective verbal behavior (i.e., communication) and coordination, are both crucial aspects that must be handled with finesse if the synthetic teammate (i.e., automation) is to be considered a team player [10], [11]. Through analysis of the team's verbal behaviors we indicate which specific verbal behaviors are viewed as important predictors of team performance.

This paper is outlined as follows. First, we review and describe the overall project of developing a cognitively plausible synthetic teammate that can interact with real human teammates. An explanation of how communication and coordination occurs during this human-automation interaction is presented. Next, we highlight the methodology for this specific study. Finally, we present the findings and analytical techniques used to determine which verbal behaviors are predictors of team performance.

II. Background

A. Synthetic Teammate

In collaboration with government entities, an ongoing goal of this larger project has been to develop a cognitively plausible synthetic teammate that can serve as a fully operational teammate. A more specific goal is to create a synthetic teammate that is able to function successfully in a three-agent Unmanned Aerial Vehicle (UAV) ground control crew.

One of the critical aspects of the project is the development of a synthetic teammate based on the ACT-R computational model [9]. Thus, the ACT-R model served as the base for one of the team members, a cognitively plausible (i.e., emulating human-like) synthetic teammate which will hopefully replace human UAV pilots in three-agent UAV ground control crews [9]. The ACT-R amalgamates declarative memory (for knowledge of facts) and procedural memory (for skilled behavior). In this sense, five key components were implemented and integrated with ACT-R: 1) language analysis, 2) language generation, 3) dialog modeling, 4) situation modeling, and 5) agent-environment interaction. However, even with the utilization of highly advanced modeling techniques, the current model lacks many human-like behaviors, resulting in a myriad of constraints during interactions with human teammates [10].

B. Team Coordination in Human-Automation Teaming

In this current study, there were three different, interdependent teammates within an UAV team; each with the unique role of taking good photos of target waypoints: 1) Air Vehicle Operator (AVO or pilot) – controls the UAV's heading, altitude, and airspeed; 2) Data Exploitation, Mission Planning, and Communications (DEMPC or mission planner) – provides a dynamic flight plan as well as speed and altitude restrictions; and 3) Payload Operator (PLO) – monitors sensor equipment, negotiates with the AVO, and takes photographs of target waypoints [12].

Also, there were three conditions: 1) the synthetic condition–the AVO role was given to the synthetic teammate; 2) the control condition–the AVO was an unexperienced human participant just like the other participants (PLO and DEMPC); and 3) the experimenter condition–one of the experimenters served as an expert AVO. The experimenter focused only on providing structured coordination to the team members. That is, in experimenter condition, the AVO asked questions to other team members to ensure timely and adaptive passing of information at target waypoints. The interaction (i.e., communication and coordination) between these three team members (the UAV team) occurs over a text-based communications system, and the team's goal is to take photographs of ground targets. To achieve this, communication must occur among the synthetic teammate and human team members in a correct way. That is, the messages sent from human teammates must not be ambiguous or cryptic, because the synthetic teammate's limited language capability may cause it to take longer (or even fail) to understand the current situation [10].

In this research, team members coordinate with each other based on three special kinds of communication–coordination events– which can occur during the missions (see Figure 1) [13]: Information (I), Negotiation (N), and Feedback (F). The DEMPC first provides (I)nformation about the upcoming target waypoint to the AVO. Next, (N)egotiation, occurs between the PLO and the AVO regarding an appropriate altitude and airspeed for the target's required camera settings. Finally, (F)eedback is sent by the PLO to other team members about the status of the target photo. These coordination events, "*INF*" for short, are then used for analysis of team coordination that is focused on how the team members interact [14]. Coordination is dependent upon communication in such a way that if communication fails, then team performance suffers. Essentially, team members must pay close attention to providing the AVO with information correctly in order to create stable communication and ensure effective team performance.

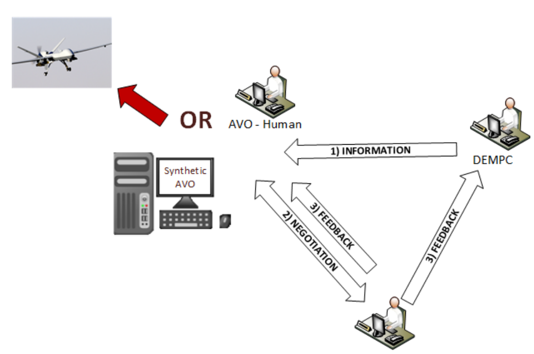

Figure 1. Coordination Events: Information-Negotiation-Feedback

C. *Team Communication in Human-Automation Teaming*

There are eight different team communication behaviors that are associated with coordination, all considered in this study (see Table 1) [4], [15]. These team communication behaviors help to understand the coordination process of human-automation teaming.

TABLE 1. TEAM COMMUNICATION BEHAVIORS

Behaviors	Description
General Status Updates	Informing other team members about current status (i.e., *From AVO to PLO*: The airspeed for the current target is 300).
Repeated Requests	Requesting the same information or action from other team member(s) (i.e., *From AVO to DEMPC*: What is the next waypoint after the current waypoint?).
Inquiry about Status of Others	Inquiring about current status of others, and expressing concerns (i.e., *From AVO to PLO*: Do we have a good for the current target?).
Suggestions	Making suggestions to the other team members (i.e., *From PLO to AVO:* Increase the altitude above 3000 for the current target.).
Planning Ahead	Anticipating next steps and creating rules for future encounters (i.e., *From DEMPC to AVO*: The next waypoint is F-AREA. It is a target. The altitude is 3100 and the airspeed 180. The radius is 2.5).
Positive Communication	Helping out team members by providing information and acknowledgement of member's speech (i.e., *from PLO to DEMPC*: please give the next target information to the AVO).
Negative Communication	Argument among the team members due to conflicting goals or incorrect destination (i.e., AVO and DEMPC can argue over the best way to give next waypoints restrictions.
Unclear Communication	Sending information with misspellings and ambiguous terms which experimenters cannot understand (i.e., *From DEMPC to AVO*: The next is F-area = target. A=180. No alt. restr. R=5).

Based on each role within the team and the coordination sequence, the team communication behaviors can be used in a structured way to result in the most effective communication and coordination. Each role's expected team communication behaviors are outlined in Table 2.

TABLE 2. EXPECTED TEAM COMMUNICATION BEHAVIORS BASED ON THE ROLE

1) DEMPC/ (I)nformation:	2) AVO/ (N)egotiation:
➢ *Planning Ahead* : providing the information about the upcoming target waypoint in a timely manner ➢ *Positive Communication*: providing additional information if it is needed by other team members	➢ *General Status Updates*: sending current altitude and airspeed to the PLO ➢ *Inquiries to Others:* inquiring feedback about having good photo
3) PLO/ (N)egotiation:	**4) PLO/ (F)eedback:**
➢ *Inquiries to the Others*: asking questions about the process of the altitude and airspeed ➢ *Positive Communication:* providing additional information about altitude and airspeed ➢ *suggestions:* suggesting to the AVO about changing altitude and airspeed	➢ *General Status Updates:* acknowledging the accomplishment of the current task to the other team members ➢ *Suggestions:* suggesting to others team members to move next waypoint

Each of these team communication behaviors and their subsequent usage within each different team member role have the ability to increase or decrease team performance. With this in mind, the *purpose* of this study is to analyze the team communication behavior data in a way that allows us to indicate which required, role-dependent team communication behaviors best predict team performance scores.

There are significant differences in expected communication behaviors between the synthetic and experimenter condition. In the synthetic condition, the synthetic teammate's lack of communication ability can affect the human team members' communication behavior. Therefore, the expected communication behaviors of the team members in the synthetic condition can be different than the communication behaviors that are depicted in Table 2. In Table 3, under the synthetic condition section, it is expected that the behavior of repeated request plays an important role. This is due to the teammates having to overcome communication discrepancies on the part of the synthetic teammate. In the experimenter condition, it is assumed that the team members will primarily engage in the communication behaviors outlined in Table 2, because information is pushed and pulled from other team members in a structured and timely manner.

TABLE 3. EXPECTED TEAM COMMUNICATION BEHAVIORS FOR EACH ROLE AND CONDITION

(a) Synthetic Condition		(b) Experimenter Condition	
1) DEMPC/ I:	**2) AVO/ N:**	**1) DEMPC/ I:**	**2) AVO/ N:**
➢ *Plan. ahead* ➢ *Positive comm.* ➢ *Inquiries* ➢ *Repeated Requests*	➢ *Gen. Stat Upd.* ➢ *Inquiries* ➢ *Repeated Requests*	➢ *Plan. Ahead* ➢ *Positive comm.*	➢ *Gen. Stat upd.* ➢ *Inquiries*
3) PLO/ N:	**4) PLO/F:**	**3) PLO/ N:**	**4) PLO/F:**
➢ *Positive. comm.* ➢ *Inquiries* ➢ *Repeated Requests* ➢ *Suggestions*	➢ *Gen. stat Upd.* ➢ *Suggestions*	➢ *Inquiries* ➢ *Positive comm.* ➢ *Suggestions*	➢ *Gen. Stat upd.* ➢ *Suggestions*

III. Methodology

A. *Participants*

Each of the conditions (i.e., synthetic, control and experimenter) were composed of ten teams for a total of 30 teams. For the experimenter and synthetic teammate conditions, two participants per team were recruited for the PLO and the DEMPC roles, and the role of AVO was played by either a trained confederate (experimenter condition) or synthetic teammate (synthetic condition).For the control condition, three participants per team were recruited. Thus, seventy participants in total were recruited from large Southwestern University, and completed the experiment. Each team participated in one seven-hour session, and each individual was compensated for participation by payment of $10 per hour. Participants ranged from 18 to 38 years of age (M_{age}=23.676, SD_{age}= 3.294), and 60 were male and 10 were female. The teams were composed of undergraduate and graduate students.

B. Equipment and Materials

The experiment was conducted in the context of the Cognitive Engineering Research on Team Tasks Laboratory, Unmanned Aerial Vehicle - Synthetic Task Environment (CERTT UAV-STE). This controlled environment is used to simulate many teamwork related aspects of UAV operations. In this experiment, the CERTT-UAV-STE software was embedded in an updated version of the hardware infrastructure (CERTT-II) which has varied features: (1) text chat capability for communications between team members; and (2) eight new hardware consoles: four consoles for up to four team members and another four consoles for two experimenters who oversee the simulation, inject roadblocks, and make observations (see Figure 2) [12].

Two experimenter consoles were used in this experiment: 1) the "texting experimenter" console has two embedded computers through which the experimenter can give ratings (for taskwork relatedness, behavior, and situational awareness) and send text messages via chat window to the other three roles (AVO, DEMPC, and PLO), and this console can also turn on and off all the computers and software of the other consoles via a master control window; and 2) the "non-texting experimenter" console, which enables the experimenter to give ratings (for coordination, taskwork relatedness, and behavior) and can also follow the participants using a camera.

Figure 2. CERTT-II Consoles

In addition to the consoles, a series of tutorials was designed in PowerPoint for training the participants. A custom software was used for collecting individual data. Furthermore, a "cheat sheet" and supplemental materials were provided to the participants: role-specific rule summaries, screenshots of each station's displays, waypoint sign list for the DEMPC, and camera setting list and photo folder comparisons of good and bad photos for the PLO.

C. Tasks and Roles

As previously noted, the CERTT UAV-STE task requires three heterogeneous and interdependent team members (each with a different task position) to complete the task of photographing critical waypoints (Figure 3): (1) the DEMPC produces a dynamic flight plan and communicates speed and altitude restrictions, (2) the AVO controls the UAV's heading, altitude, and airspeed, and (3) the PLO monitors sensor equipment and photographs ground targets [12]. Prior to arriving at the session, team members were randomly assigned to one of these three roles (in the control condition; in the synthetic and experimenter condition, only the DEMPC and PLO were eligible for assignment), which they retained during the experiment. There are five missions in this study. Each mission required teams to photograph 11-20 targets in 40 minutes or less. During the missions, teams were instructed to obtain as many 'good' photos as they could while avoiding alarms and violations of rules. Each mission terminated either at the end of a 40-minute interval or when team members believed that the mission goals – taking a good photo for each target– had been completed.

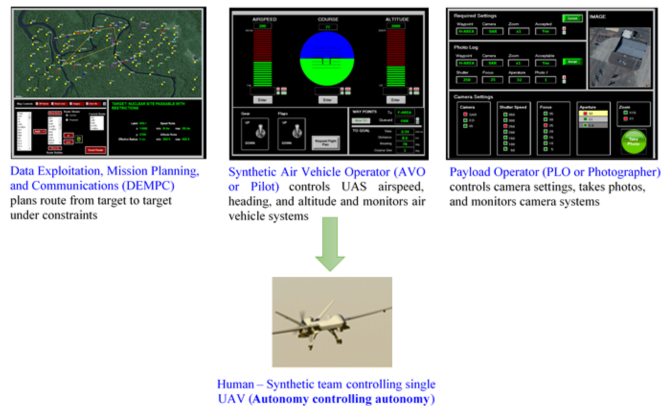

Figure 3. The UAV-STE Team Roles

D. Measures

Several measures were considered in this study, including a team performance score that was calculated at the target and mission level based on the timely and accurate processing of the target. Additional measures included team process measures of communication (message count and flow), a verbal behavioral checklist, team coordination, process ratings, team situation awareness, and responses to a post-experiment questionnaire and the NASA-TLX workload questionnaire. Due to the overall focus of this paper, this report focuses on measures of verbal behaviors.

Team communication behaviors (verbal behaviors) are noted instances of a set of verbal behaviors associated with team coordination: negative communication, positive communication, repeated requests, unclear communications, general status update, inquiry about status of others, planning ahead, and suggestions to others (as previously outlined). Two experimenters code each communication, giving the communication a 1 if it matches that behavior type, or a 0 if it does not. If one experimenter codes it as a 1 and the other as a 0 for a specific behavior then both codes are averaged to be a code of .5. Each communication may be coded for more than one behavior, or none at all. Therefore, team communication behaviors were recorded by two experimenters during the experiment. Study inter-reliability was also tested to see if there is an agreement between both experimenters on recording the verbal behaviors.

Team performance score (mission-level) is a composite of mission variables, including the rate at which targets are successfully photographed, the time each individual spends in alarm and warning states, and the rate at which critical waypoints are acquired.

E. Experimental Session

During the experiment, the DEMPC and the PLO were isolated in one room, and they were seated in locations separated by partitions to prevent face-face contact. The AVO was in another room. During the eight-hour experimental session, each team completed five – 40 minute missions in which they photographed targets (see Table 4).

TABLE 4. EXPERIMENTAL SESSION

Sessions	
1) Consent forms	**7)** Mission 3
2) PowerPoint Training	**8)** Mission 4
3) Hands on Training Mission	**9)** Mission 5
4) Mission 1	**10)** NASA TLX/ Knowledge
5) NASA TLX / Knowledge	**11)** Demographic questions/ debriefing
6) Mission 2	**12)** Post Checklist

IV. Analysis

With such a large number of verbal behavior variables across the different roles, a method for reducing that number was needed to achieve a concise model of team performance. For this purpose, the LASSO (Least Absolute Shrinkage and Selection Operator) statistical method was used to select the team communication behaviors that were the best predictors of team performance. LASSO is not a theory-driven, but data-driven method, and the team communication behaviors selected by this method might be useful to further explain team performance scores. This paper is not focused on reporting the team performance scores, rather investigating what team communication behaviors are the best predictors of good and poor performance.

LASSO works by creating a penalty function which is the residual sum of squares (RSS) [16], [17] in the regression equation plus an additional term. This additional term is calculated by multiplying the absolute sum of the regression coefficients with the tuning parameter, lambda (λ) that is obtained by using a cross validation approach. Larger values of lambda forces weaker coefficients down to zero. More explicitly, LASSO finds regression coefficients betas (β) that minimize the following equation [17]:

$$\sum_{i=1}^{n}\left(y_i - \beta_0 - \sum_{j=1}^{p}\beta_j x_{ij}\right)^2 + \lambda\sum_{j=1}^{p}\left|\beta_j\right| = RSS + \lambda\sum_{j=1}^{p}\left|\beta_j\right|. \qquad (1)$$

where $\lambda \geq 0$. This tuning parameter controls the relative impact of the RSS and the shrinkage penalty ($\sum_{j=1}^{p}|\beta_j|$). Therefore, when $\lambda = 0$, the penalty term has no effect, but when the value of λ increases, then the shrinkage penalty increases. As a result, the irrelevant regression coefficients get closer to zero [16]–[18].

We divided the dataset into two datasets: one for training and one for testing. First, the LASSO method was used on the training dataset, removing the irrelevant predictors from the model. In the second step, the regression coefficients obtained from the training dataset were used on the test dataset to determine how well the model fits the data. To minimize overfitting, we used cross-validation to choose the optimal lambda. Figure 4 shows the plot for selecting the optimal lambda to get a log (lambda) value between the two dotted vertical lines.

V. Results and Discussion

A. Inter-rater Reliability Test

Cohen's κ was run to determine if there was an agreement between two experimenters' observations on recording the teams' communication behaviors. There was substantial agreement between the two experimenters' observation, κ = .774 (95% CI, .754 to .794), p < .001.

B. LASSO Results

The optimal λ that minimizes the cross validated mean squared error on the training data is 2.062138 (see Figure 4), and RSS is 55.51352. The results based on fitting the training model to the test data showed that the regression model for team communication behaviors explained 27% of the variability of team performance.

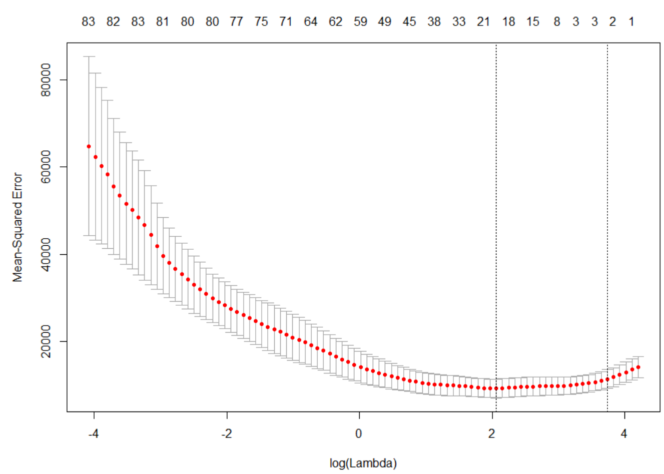

Figure 4. The Optimal Lambda for LASSO by Applying Cross Validation Plot

With λ = 2.062138, the LASSO method was applied on the sample data, which returned 16 role related communication behaviors, which are categorized as the best predictors of team performance (see Tables 5, 6, and 7). Each vertical line in Figure 5 represents each predictor and their coefficients. The doted vertical line in Figure 5 demonstrates the optimal λ value.

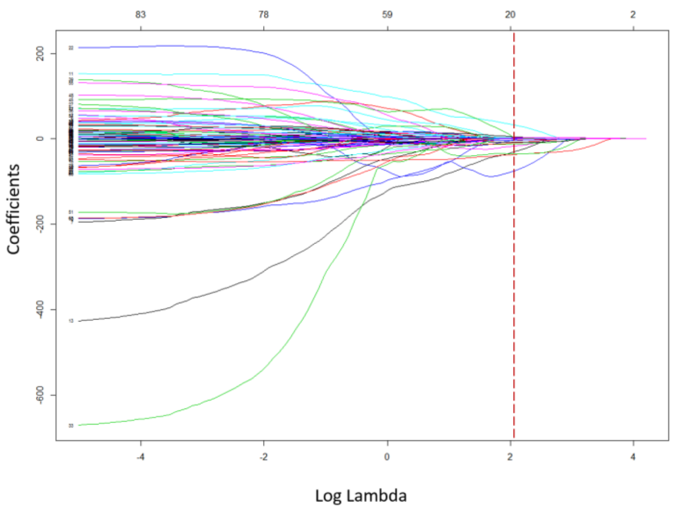

Figure 5. Cross Validation Plot to Find the Optimal Lambda with the Greatest Amount of Shrinkage

In general, the findings across all teams (see Table 5) show that *Unclear* (given by DEMPC and AVO) and *Negative* (given by PLO) *Communication* occurred between team members, and are negatively related with team performance. However, the majority of expected behaviors which were proposed as being essential for effective communication (see Tables 2) were not selected as being critical predictors of team performance by the LASSO method.

Looking more specifically at the role based communication behaviors we can see that *General Status Updates* and *Positive Communication* from DEMPC are negatively related with team performance. As to be expected, *Unclear Communication* from the DEMPC is negatively related with team performance. However, more surprising, is that *Positive Communication* is viewed as a negative predictor to team performance. This may be due to the DEMPC's role in dynamic situations wherein they must help the team complete the current task (e.g., the synthetic teammate might have crashed or the team couldn't achieve the task on time). This often results in the DEMPC overstepping their perceived role within the team, which may negatively influence the other team members' perception of the DEMPC in general.

TABLE 5. LASSO RESULTS (COEFFICIENTS) FOR TEAM COMMUNICATION BEHAVIOR FOR OVERALL TEAMS

1) DEMPC/ I	**Coefficients**	**3) AVO/ N**	**Coefficients**
➢ *Gen. Sta. Update*	**-2.754**	➢ *Inquiries*	**1.195**
➢ *Positive Comm.*	**-11.752**	➢ *Plan. ahead*	**1.554**
➢ *Unclear Comm.*	**-36.232**	➢ *Unclear comm.*	**-7.607**
		➢ *Suggestions*	**-3.199**
3) PLO/ N	**Coefficients**	**4) PLO/F**	
➢ *Negative Comm.*	**-9.088**	➢ N/A	

According to the findings related specifically to the AVO across all conditions, the verbal behaviors of *Inquiries* and *Planning Ahead* were predictive of positive team performance. *Inquiries* communication generally means that the AVO was inquiring for feedback regarding having a good photo (i.e., from AVO to the PLO: Do we have a good photo?). However, *Planning Ahead* is expected to be conducted by the DEMPC, because the DEMPC is the one who is in charge of planning waypoints. In this case, it is possible that in the experimenter and/or control conditions, the AVO may have become involved with *Planning Ahead.* Yet, the AVO's *planning ahead* verbal behavior is not shown at the condition level (i.e., synthetic and experimenter).

Findings at the condition level show a myriad of different findings. Focusing on the differences between the synthetic and experimenter conditions is particularly interesting. In the experimenter condition, when the team members follow expected communication behaviors (proposed in Table 3), it is clear that the behaviors are effective predictors of positive team performance. When the expected communication behaviors are not followed, negative predictors of team performance are apparent. However, in the synthetic teammate condition, some of the expected team behaviors used by human teammates show a negative relationship with team performance, because of the synthetic teammate's lack of human-like behavior.

The results of the experimenter condition show that *Planning Ahead* by the DEMPC, the AVO helping out other team members (*Positive Communication*), and *Inquiries* to other team members by the AVO are positive predictors of team performance (Table 6). However, and unsurprisingly, the DEMPC's *Negative Communication* was selected as a predictor in the experimenter condition, and as expected it was a negative predictor to team performance. Interestingly, there is no relationship between information pushing (i.e., *General Status Updates*) and team performance in the experimenter condition, and, likewise no relationship of any of the PLO's verbal communication with team performance.

Pushing information by the AVO during negotiation is crucial for coordination, and the overall accomplishment of the task. In this case, the relationship of inquiries with team performance is highly substantial if the other human team members do not complete their role requirements correctly. For instance, if the AVO inquiries about other team members (information from DEMPC, and required airspeed and altitude restrictions from PLO), then the effect of the *Inquiries* will be higher than *General Status Updates*. The AVO's inquiries could also force the DEMPC to send more information during the task, which may address the DEMPC's negative communication effect, and also the DEMPC's need to send more information about upcoming waypoints. Therefore, in general, the AVO's pulling and pushing information in a timely manner caused some structural changes on the coordination such as increasing *Negative Communication* and *Planning Ahead* while also lessening the PLO's verbal communication behavior.

TABLE 6. LASSO RESULTS (COEFFICIENTS) FOR VERBAL BEHAVIOR FOR EXPERIMENTER CONDITION

1) DEMPC/ I	**Coefficients**	**4) AVO/ N**	**Coefficients**
➢ *Plan. Ahead*	**5.247**	➢ *Positive Comm.*	**1.868**
➢ *Negative Comm.*	**-74.878**	➢ *Inquiries*	**2.874**
3) PLO/ N	**Coefficients**	**4) PLO/F**	**Coefficients**
➢ N/A		➢ N/A	

As previously noted, in the synthetic teammate condition, when some of the expected team behaviors (Table 3) are used correctly by teammates they are indicated as negative predictors of team performance. Note that this is a completely opposite finding of the experimenter condition. This in itself is an interesting finding and one that we think can be explained due to the synthetic teammate's lack of human-like behavior, subsequently causing discrepancies in team communication and coordination.

Looking further at the synthetic condition, the findings show that *Repeated Requests* by the DEMPC, *Negative Communication* by the PLO, and *Positive Communication* by the PLO all were viewed as predictors of worse team performance. *Negative communication* is not expected by the PLO. One of the reasons behind repeated requests and positive communication for the synthetic teammate condition is directly tied to issues relating to trust in automation [19]. Due to the synthetic teammate's lack of human behavior, the human team members might not fully trust the automation.

Only *General Status Updates* from the AVO were positively related with team performance. Overall, the synthetic condition results show that the synthetic teammate changes the communication behavior of the human team members.

TABLE 7. LASSO RESULTS (COEFFICIENTS) FOR VERBAL BEHAVIOR FOR SYNTHETIC CONDITION

1) DEMPC/ I	**Coefficients**	**5) AVO/ N**	**Coefficients**
➢ *Repeated requests*	**-1.011**	➢ *Gen. Stat. Upd.*	**3.590**
3) PLO/ N	**Coefficients**	**4) PLO/F**	**Coefficients**
➢ *Positive Comm.*	**-2.979**	➢ N/A	
➢ *Negative Comm.*	**-34.904**		

VI. CONCLUSION

In this study, we have outlined the importance of both communication and coordination in human-automation teaming. More specifically, we investigated the role of different team communication behaviors (verbal behaviors) when a synthetic team member is communicating with other real human team members. The LASSO (Least Absolute Shrinkage and Selection Operator) method was used to select the team communication behaviors that were the best predictors of team performance. Through analysis, it is apparent that there are specific communication behaviors (at both the role and condition level) that are predictors of team level performance. In general, negatively perceived behaviors are predictors of negative team performance. Through this study we also learned that even when team members follow their optimal and expected communication behaviors when communicating with a synthetic teammate, these behaviors are still predictors of negative team performance. This is an important future consideration: even if human team members are properly communicating with a synthetic teammate, its errors and lack of human-like behavior can still result in a negative effect on team performance.

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