# The Impact of Perceived Autonomous Agents on Dynamic Team Behaviors

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# The Impact of Perceived Autonomous Agents on Dynamic Team Behaviors

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***Abstract*—Adaptive complex team behaviors evolve dynamically and occur in many different environments. In this study, we examined the role of these behaviors and their relationship with team performance in the context of human-autonomy teams (HAT) and all-human teams. The HAT served as the "synthetic" condition in which two human team members were informed that the third team member was a "synthetic" agent; in the control condition, the team members were informed that the pilot was a remotely located human teammate. Following are the primary findings from this study: first, control teams demonstrated better performance than the synthetic teams; second, control teams were more active than the synthetic teams in terms of planning the task, and third, the behavioral passiveness of the synthetic teams (due to lack of planning) associated with diminished team performance. This suggests that the synthetic teams did not show enough adaptive complex behaviors that were evident in control teams. This finding implies that merely believing the pilot to be a synthetic agent made it more difficult for synthetic teams to plan and, thus, effectively anticipate their teammates' needs. In addition, this study highlights that there is a significant need for humans to gain experience in working with a synthetic agent to overcome negative perceptions.**

***Index Terms*—Autonomous agent, human-autonomy teams, nonlinear dynamical systems, synthetic agent, teamwork.**

## I. Introduction

DYNAMIC team behaviors emerge as a result of self-organization among interdependent team members in dynamic task environments in which a dynamic task is characterized by an environment that changes over time, e.g., Command-and-Control, and surgical rooms. This means that interaction patterns of the team are a self-organizing property created by the individual team members' behaviors and these patterns are uniquely possessed by the team/dynamical system as a whole (not the individual members∼more than the sum of its properties) [1]. A team's dynamic behaviors can also be determined by interactions with the dynamic task environment which contains a great deal of uncertainty [2]. This uncertainty in the environment must be reflected in the team's unpredictable behaviors, if they are to achieve their team-level goals [3]. This is especially true in complex task environments in which behavior must be adaptive and resilient in response to the dynamical chances within the team (as local) and the task environment (as global system) [4].

In these type of complex dynamic environments with ill-structured problems, uncertain dynamics, action/ feedback loops and time constraints, agents are becoming commonplace in training simulator systems [5] and real environments, e.g., using robots for hazardous environments. According to Artificial Intelligence (AI) researchers, an autonomous agent (e.g., synthetic software based agent and robot) is a form of actor/entity which has three main characteristics: the ability to obtain inputs through sensing, the ability to make decisions, and ability to execute the selected action [6]. In this article, when we refer to an autonomous agent, we are referring to a synthetic software based agent grounded in Computational Intelligence (CI) capabilities.

Increasingly, human team members' work involves interactions with autonomous agents. More specifically, in recent years, technological advances have allowed for autonomous agents to take on the role of a teammate [7], and this has led to research interest in Human-Autonomy Teaming (HAT) [8]. However, building an autonomous agent as a team member is still challenging and requires understanding human intelligence from the perspective of cognitive, behavioral, physiological, and other psychological processes [9]. An autonomous agent may benefit teams by reducing workload, but the agent's limited natural language abilities may also harm teams by increasing cognitive demands on the human teammates, which could, in turn, negatively affect team situation awareness and performance [8], [10], [11]. In addition, humans are accustomed to interacting with other humans in the complex dynamic environment. Therefore, building HAT also requires understanding how human team members interact with an autonomous agent as a team member [8].

In this research, we simulated a synthetic agent with natural language (that is, human-equivalent) and learning abilities by having a human in the role of "synthetic agent". This was achieved by manipulating the beliefs of the other two team members such that they believed the third team member was a synthetic agent. The main question is whether the manipulation of this belief can affect team interactions and ultimately effective team performance. One of the aims of this study is to use Nonlinear Dynamical Systems (NDS) methods to understand and explain the adaptive complex behavior of HAT which occurs via the interactions among human and synthetic agent team members. In this case, we use team communication flow

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and team verbal behavior (as aspects of team interaction) to predict teams' Target Processing Efficiency (TPE), which is a coordination-related score.

In the current study, first, we review the literature regarding HATs and NDS, and then, describe the experimental design of the study. Next, we present the findings and analytical techniques used to determine the dynamics of the relationship between team interaction patterns and TPE across the teams over time. Finally, we discuss how to build mechanisms to make HAT more effective in the future.

## II. Literature

### A. From All Human to Human-Autonomy Teams

A full/semi-autonomous agent is an intelligent system that can wholly (or partially) direct its own functions outside of the situations that it was designed for [12]. In general, autonomous agents have the ability to: achieve goals independently, use verbal and non-verbal communication behaviors to perform better in dynamic environments, and self-correct in the event of system failures [12]–[14]. However, it is difficult to say whether an autonomous agent meets the human standard of being a team member.

In general, a team may be defined as two or more heterogeneous and interdependent individual members who mutually seek to achieve some common goal [15]. In this case, one characteristic of teamwork is, basically, how well the team members are doing with each other by adapting to their task environment. That is, teamwork is the class of behaviors that arise from several individuals coordinating and collaborating on interdependent tasks while working towards a common goal [16]. Based on these definitions, a substantial body of literature on human teams identifies some features of teammates relevant to a team's success [17]: interdependence with other teammates [18], effective interaction -communication and coordination- with other teammates and task environment [19], shared common goals [20], meeting teammates' needs [9], shared mental models [9], fulfilling their roles [21], trust in each other [22], and situation awareness during routine and novel situations [23].

However, in general, creating an autonomous agent that possesses such ideal characteristics is not easy for the AI researchers. Yet, thanks to recent advances in the AI and robotics fields [24], there is promise that an autonomous agent can be a teammate [25] if the correct intelligence capabilities are programmed. Specifically, the agent needs to have some team cognitive processing abilities (e.g., team mental models, team situation awareness, sense making) and, most importantly, team interaction capabilities. These abilities are especially important in dynamic contexts which implicitly require team members to interact (verbally or non-verbally) over time if they are to continuously learn during the task [26]. These abilities allow for the agent to develop and articulate a shared understanding (via shared knowledge) of its teammates by effectively interacting with them and its task environment as they jointly move towards a common goal. When such an autonomous agent acts as a teammate with one or more humans, the hybrid team is called a HAT. HATs are dependent on human team member(s) interdependently interacting over time with an autonomous agent to successfully achieve a common goal [27], [28]. One of the recent studies about HAT (in which the autonomous agent had limited communication abilities) found that interactions among the team members and their interaction with their task environment are generally nonlinear (not proportional) and lead to predictable team dynamics over time [26], [29], [30]. These extremely predictable dynamics of the HAT resulted in poor team performance [29].

The main question is: if the synthetic agent has natural language and learning capabilities, how will overall team interaction and its relationship with the performance change over time? To answer this question, we will view teams as complex systems, which involve several characteristics: team members as agents, their interactions among each other and with their environment, self-organization and emergence within the team to create behavioral patterns. These characteristics can be observed better via the NDS perspective and related methods.

### B. Emergent Properties of Teams as Nonlinear Dynamical Systems

In general, a dynamical system—such as a team—is a system that continuously evolves via its behavior, which is an emergent product of its elements interacting over time [31]. A system and external forces mutually interact to produce emergent stable patterns. Many patterns of behavior can emerge, and transitions between patterns are often sudden and nonlinear [32]. A nonlinear dynamical system can behave in many ways, but all its possible behaviors fall within what is called a multidimensional "state space". Due to the actions of its constituent parts and external forces, the system may behave differently over time—that is, move around the state space. If the system develops some patterns of behavior that are reliable, that means it is favoring a region of the state space and it is said to have moved into an "attractor state". Even if it moves away from the attractor state, the system will likely return to it again later [33]. As the system gains experience, the attractor states grow more stable and the system becomes more resistance to perturbations. Nevertheless, the system remains exposed to the external forces of the environment which can move the system into new patterns of behavior given a strong enough perturbation [33], [34].

A team is an example of a nonlinear dynamical system, as it emerges via the interactions between team members (be they humans or autonomous agents). Each team member follows their individual roles, but must also synchronize that role with the other team members in a timely manner to achieve a common goal or task. This leads the team to produce an emergent complexity which is robust, flexible, and fault-tolerant over time, whether under routine or novel conditions [35]. As an example, Fig. 1 shows an Unmanned Air Vehicle (UAV) ground station team which produced an emergent complex behavior over time in order to effectively control a UAV. This new behavior also leads to entirely new system behavior in response to the dynamic task environment.

The interactions among the team members change over time, and thus, they are nonlinear [26], [36]. This nonlinearity leads

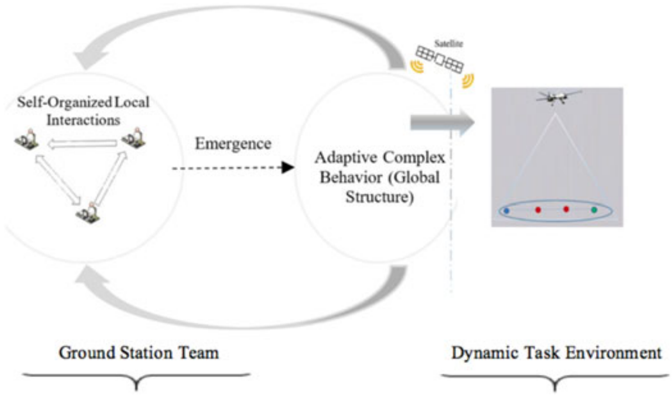


Fig. 1. A network representation of adaptive complex behavior which emerged from a ground station team via self-organized local interaction to control the Unmanned Air Vehicle in the dynamic task environment. The dashed line indicates two different environments: the ground station and the dynamic task environment.

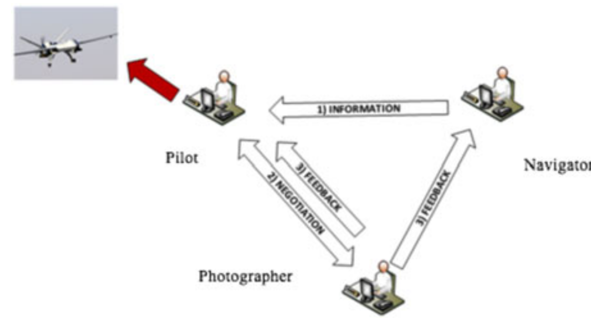


Fig. 2. Team Coordination (Information-Negotiation-Feedback) in simulated Command-and-Control (C2) task environment (Modified from [10]).

to team research within the realm of Nonlinear Dynamical Systems (NDS). With NDS methods, it is also possible to measure dynamical changes of a team's complex behavior between team members and with its task environment.

In previous team research, NDS methods have been applied to human teams to measure interactions among team members and with their task environment. In those studies, one of the nonlinear dynamic modelling concepts was Recurrence Quantification Analysis (RQA), quantifies the number of recurrences (and their length) present using a phase space trajectory in a dynamical system [37]–[40], [41]. A multivariate extensions of RQA, called Joint Recurrence Quantification Analysis (JRQA), measures a system as a whole rather than its individual separate parts [42]. JRQA basically assesses synchronization between interacting systems, and also assesses the systems that can jointly influence one another [43]. Within the team concept, JRQA can be used to examine variation in dynamics across teams. Recent studies [44], [45] have used JRQA to measure a team as a system, and their findings indicate that teams should be flexible and stable for best performance. In the current study, we only apply the JRQA technique to team communication flow in order to capture behavioral dynamics of all-human and human-synthetic teams.

## III. Methodology

### A. Design Summary

In a synthetic Unmanned Aerial Vehicle (UAV) environment heterogeneous teams of three members (pilot, navigator, and photographer) were required to take good photos of critical target waypoints during simulated missions by interacting with each other via text-chat. In this task, photos are considered "good" if they were taken with the proper camera settings and corresponded with the photographer's supplied library of good photos. The required interaction among team members at critical target waypoints is as follows: (1) the navigator produces a dynamic flight plan with speed and altitude restrictions of waypoints, and sends this *information* to the pilot; (2) the pilot controls the UAV in terms of heading, altitude and airspeed, and then *negotiates* with the photographer about altitude and airspeed; (3) the photographer adjusts camera settings based on the current altitude and airspeed, and photographs ground targets, and after that sends *feedback* to other team members regarding they have a good photo of the target; see Fig. 2 [46]. In short, this coordination sequence is called Information-Negotiation-Feedback (INF).

Two conditions were considered in this research: (1) *the "synthetic" condition*, in which the navigator and photographer were informed that the pilot was a "synthetic agent"; and (2) *the control condition*, in which the team members were informed that the pilot was a remotely-located human teammate. In reality, the pilot in each condition was a human, meaning that the only difference across conditions was the description of the nature of the pilot teammate, and thus the beliefs of the navigator and photographer about the pilot. In this case, one synthetic agent (pilot) communicated and coordinated with two human team members in order to achieve the team task. In both conditions, the pilot was able to communicate via text chat using unencumbered natural language and was uninformed about the manipulation (i.e., had no reason to think he should be agent-like).

In the simulated task environment, participants were instructed to effectively interact with each other by providing (pushing) and requesting (pulling) information and had to develop the proper timing of giving information to their intended recipient. If each teammate is properly anticipating the other teammates' needs, very few requests for information should be observed [47].

With that in mind, in the current study, we address the following two questions: (1) what is the nature of team interaction in the HATs and all-human teams?; and (2) how is team interaction associated with the performance in HATs and all-human teams?

### B. Participants

Sixty randomly selected participants (20 teams) were recruited from Arizona State University and surrounding areas, completed the study and were compensated for participation with a payment of \$10 per hour for the eight-hour experiment. Participants were required to be fluent in English and have normal or corrected-to-normal vision. Ages ranged from 18 to 48 ($M = 23$, $SD = 6.39$), with 34 males and 26 females.

TABLE I
EXPERIMENTAL SESSION

| Sessions | |
|---|---|
| I) Before Task | (1) Consent forms, |
| | (2) PowerPoint training, |
| | (3) Hands on training. |
| II) Task | (4) Mission1, NASA TLX I/ Team Knowledge I, |
| | (5) Mission2, Mission3, Mission4, Mission5, and NASA TLX II/ Team Knowledge II. |
| III) After Task | (6) Demographic questions, |
| | (7) debriefing, and |
| | (8) experimenter check list. |

### C. Materials

In this experiment, the Cognitive Engineering Research on Team Tasks - Unmanned Aerial System – Synthetic Task Environment (CERTT-UAS-STE) was used [46]. The UAS-STE features a hardware infrastructure allowing for: (1) text-chat communication between team members; and (2) four consoles for participants, and four for experimenters (two for storing the data and two for monitoring the simulation). By using their two designated consoles, experimenters are able to start and stop the missions, communicate with participants, administer situation awareness roadblocks, log team member coordination, monitor the mission-relevant displays, and observe and enter team behavior through camera and chat server.

In addition, a series of tutorials was designed in PowerPoint to train the team members. Custom software was used to administer knowledge, workload, and demographic questions and to record team process, relatedness ratings, and preference data. Each participant had a rules-at-a-glance information sheet about their individual role and the photographer had examples of good and bad photos. Other paper materials were consent forms, debriefing forms, and experimenter checklists.

### D. Procedure

The experiment procedure is depicted in Table I. In both conditions, each participant was randomly assigned to one of the three roles: pilot, navigator, or photographer. During the experiment, teams were divided into two groups: the navigator and the photographer were seated in one room (and separated by partitions such that they did not have face-to-face contact) and the pilot in another. In the synthetic condition, the pilot entered the building through a separate entrance from the navigator and the photographer. Therefore, the pilot in the synthetic condition did not meet with other team members (even during the breaks, the pilot used separate entrance). For both of the conditions, there was no interaction between the participants before the experiment. The only interaction that occurred among the participants was during the experiment and within the experiment.

Before the starting the experiment, all the participants read and signed an informed consent form. Then, participants received a briefing and then a role-specific skills training using a PowerPoint training program. After the PowerPoint training session, all the participants started a 30-minute hands-on practice training wherein the participant's performance of basic skills were assessed by the experimenters. The experimenters used a checklist to check off each skill as the participants demonstrated acceptable levels of performance on their individual tasks. Once all three members of a team had all of their skills checked off the list, the team was allowed to begin the first mission.

The experimental session lasted eight-hours which consisted of five missions (between each mission, there was a 15-minute break): Missions 1 through 4 of comparable workload and Mission 5 of high workload. The high workload of Mission 5 allows for a more sensitive measure of performance that often better discriminates good from poor teamwork. For each mission, teams were required to photograph multiple targets (between 11–20) in 40 minutes. Teams were instructed to obtain as many 'good' photos (based on correct camera settings, including camera type, shutter speed, focus, aperture, and zoom) as possible while avoiding alarms and violations of rules.

In this task, targets were demonstrated color-coded waypoints on the simulated task environment, and each target required specific photos, such as a nuclear plant or an air force base. There were 11 target waypoints for Mission 1 and Mission 3, 12 targets for Mission 2, 13 targets for Mission 4, and 20 targets for Mission 5. Target waypoints fell into areas called Restricted Operating Zones (ROZ boxes) which also include entry and exit waypoints. Mission 1 to Mission 4 contained five ROZ boxes, whereas Mission 5 contained 7 [48].

As previously noted, teammate expectations of the pilot were manipulated and treated as a between-subjects (i.e., teams) variable; and "mission" and "target" were treated as within-subjects variables (with targets nested within missions). During the experiment, participants did not have face-to-face contact, and the pilot was isolated in a separate room. The complete experimental session and its procedure are shown in Table I.

### E. Measures

*Target Processing Efficiency (TPE)* is a measure of team performance that takes into account the time spent inside a target waypoint to get a good photo. Each team started with a maximum of 1000 points. Then, waypoints were deducted equivalent to the number of seconds spent in the target radius and 200 penalty points for bad or missed photos [48]. Critical team coordination occurs at target waypoints and thus, this score reflects the quality of that coordination.

*Team Verbal Behaviors:* In this task, team coordination is comprised of several team verbal behaviors, and these verbal behaviors were classified into two groups: *pushing* or *pulling* of information among the team members (see Table II) [10], [11].

*Communication Determinism:* We applied JRQA on team communication flow (by considering message sent time to each member during the task) in order to investigate team interaction patterns and their change over time. From each of the UAV missions, several measures were extracted by applying JRQA, including: recurrence rate, determinism, longest diagonal line, entropy, laminarity, trapping time, and longest vertical line.

We selected determinism (DET) as the focal variable, and it can be defined as the ratio of recurrence points forming diagonal lines to all recurrent points in the upper triangle [41]. By showing the distribution of recurrent points, DET shows how organized a

TABLE II
CLASSIFICATION OF THE TEAM VERBAL BEHAVIORS [10]

| Behavior | Push /Pull | Description of the behavior |
|---|---|---|
| General Status Updates | *Push* | Informing other team members about current status, *e.g., airspeed for the current target is 300*. |
| Suggestions | *Push* | Making suggestions to the other team members, *e.g., increase the altitude above 2000 for the current target*. |
| Planning Ahead | *Push* | Anticipating next steps and creating rules for future encounters, *e.g., the next target is F-AREA: the altitude 2000, the airspeed 200, the radius is 5*. |
| Repeated Requests | *Pull* | Requesting the same information or action from other team member(s) *e.g. what is the next waypoint?* |
| Inquiry about status of others | *Pull* | Inquiring about current status of others, and expressing concerns, *e.g., do we have a good photo for the current target?* |

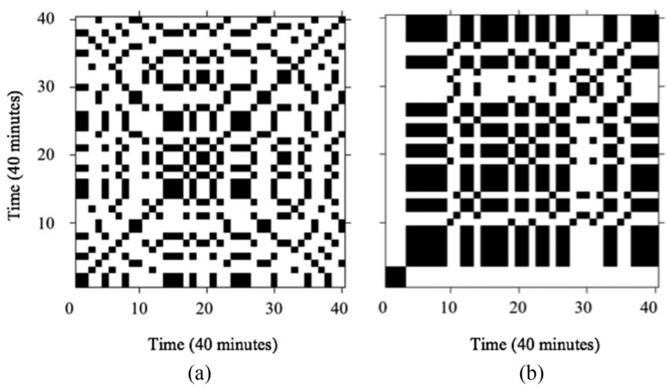


Fig. 3. Example Joint Recurrence Plots for two high performing UAV teams' interactions (length 40 minutes): (a) control (Determinism: 46%) and (b) synthetic teams (Determinism: 77.6%).

system's communication behaviors are. A highly deterministic (highly organized and predictable) system would have many sequences of repeated states, which would be represented on the recurrence plot as diagonal lines. Such diagonal lines would be less prevalent in mildly deterministic systems, but even these systems can have brief periods of repeated states [49]. DET is calculated by the following formula [41]:

$$DET = \frac{\sum_{l=l_{\min}}^{N} lP\left(l\right)}{\sum_{l=1}^{N} lP\left(l\right)} \tag{1}$$

where $l$ is the diagonal line length considered when its value is $\geq l_{\min}$ and $P(l)$ is the probability distribution of line lengths. This determinism percentage (rate) can take values between 0% (no repeats in the time series) and 100% (the time series repeats perfectly).

We applied JRQA to the multivariate binary communication flow data (i.e., sent time stamp from each UAV mission) to visualize and quantify recurrent structure in each team's communication events. In Fig. 3, we give two example Joint Recurrence Plots (JRP) for three UAV teams' interactions for three conditions (three-code sequences that are each 40-minute in length). On JRP, states of the system's epochs of similar time evaluation are the diagonal lines [50]. From this definition, chaotic (i.e., unpredictable) processes will have no (or very short) diagonals,

TABLE III
THE ANOVA RESULTS FOR TARGET PROCESSING EFFICIENCY

| Source | *df* | *F* | *p* | $\eta^2$ |
|---|---|---|---|---|
| Condition (Con.) | 1 | 7.52 | 0.01 | 0.06 |
| Mission (Mis.) | 4 | 8.17 | 0.00 | 0.18 |
| Target (within Mis.) | 49 | 3.53 | 0.00 | 0.26 |
| Con. by Target (within Mis.) | 42 | 1.50 | 0.03 | 0.11 |
| Con. by Mis. | 4 | 1.02 | 0.40 | 0.03 |

whereas predictable processes will have longer diagonals and fewer single, isolated recurrence points [41] (see Fig. 3). For instance, Fig. 3 shows two high performing teams' joint recurrence plots from each of the conditions: the control teams show less predictable team communication behavior with very short diagonals (Determinism: 46%) whereas synthetic teams show more predictable behaviors with longer diagonals (Determinism: 77.6%).

## IV. ANALYTIC PROCEDURE AND RESULTS

In response to the research questions, we first applied Analysis of Variance (ANOVA) to answer whether TPE significantly differs across the two conditions, synthetic vs control. After that, the same method was applied to the team verbal behaviors, and only significant results are briefly summarized. Finally, Growth Curve Modelling (GCM) [51] was applied on the dataset to examine whether there was a significant relationship between team interaction patterns and team communication behaviors with TPE, and whether these relationships differ across the conditions. In this study, R version 3.2.3 [52] using the "crqa" package [53] was used to carry out JRQA for calculating DET measure. In R, "lmerTest" package version 2.0–32 was used to conduct GCM analysis [54].

### A. Target Processing Efficiency Results

Target Processing Efficiency (TPE) was analyzed via a repeated measure three factor mixed Analysis of Variance (ANOVA) with condition as a between-teams manipulation and the mission and target variables nested within missions as within-teams factors. Table III summarizes the results of the mixed ANOVA.

Because there was a significant condition main effect, the follow-up pairwise comparisons (based on LSD test) indicate that the synthetic teams performed significantly poorer than the control teams, $M_{\text{Syn}} = 808$, $SD_{\text{Syn}} = 145$, $M_{\text{Cont}} = 844$, $SD_{\text{Cont}} = 134$, $p < .05$. The significant mission effect indicates an improvement in overall efficiency from Mission 1 to Mission 4 ($M_{\text{Mission1}} = 733$, $SD_{\text{Mission1}} = 190$, $M_{\text{Mission4}} = 899$, $SD_{\text{Mission4}} = 101$, $p < .001$), and then TPE significantly decreased from Mission 4 to Mission 5 ($M_{\text{Mission5}} = 793$, $SD_{\text{Mission5}} = 149$, $p < .001$). The significant target (within mission) effect, indicates that TPE increased for the first two targets, and then did not change until the last target. After that, TPE decreased at the last target. However, the two main effects of condition and target (within mission) should not be interpreted alone, as there was also a significant condition by target (within mission) interaction

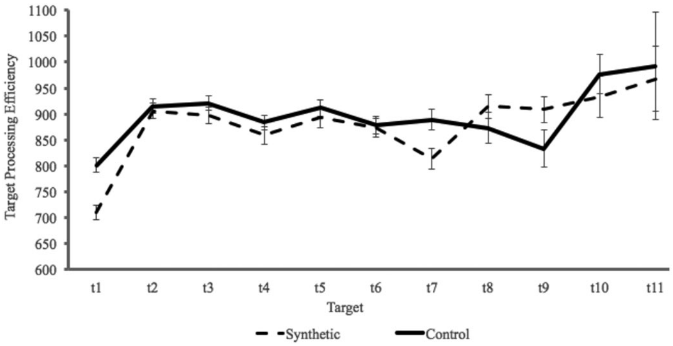


Fig. 4. Target Processing Efficiency (TPE) across the conditions and across the targets. Error bars provide the standard error of the mean (vertical lines indicate +/− SE).

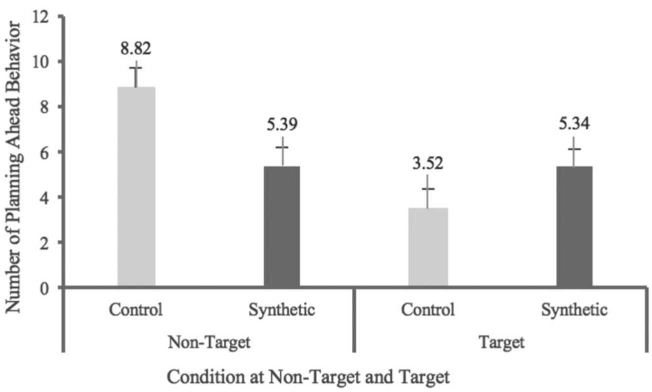


Fig. 5. Number of planning ahead behaviors across the conditions at non-target and target. Error bars provide the standard error of the mean (vertical lines indicate +SE).

($F(42, 496) = 1.50$, $MSe = 9628$, $p < .05$). This indicates that the "synthetic teams" demonstrated more stable TPE, whereas the control teams' TPE fluctuated over time; see Fig. 4.

## *B. Team Verbal Behavior Results*

Each of the team verbal behaviors, which were sent by team members during targets or non-targets, routine waypoints, were also analyzed via a repeated-measures three-factor mixed ANOVA with condition as a between-teams manipulation and the mission and target variables nested within missions as within-teams factors. Only one of the verbal behaviors showed behavioral changes across the conditions and/or across the targets. Interestingly, this change happened for pushing related verbal behavior which is *planning ahead* (see Fig. 5). Here is the statistical summary of this behavior:

The results for *planning ahead* indicates that only the interaction effect of condition by target, $F(1, 45) = 5.29$, $MSe = 37.7$, $p < .05$, $\eta^2 = .11$, and the target main effect, $F(1, 45) = 4.81$, $MSe = 37.7$, $p < .05$, $\eta^2 = .096$, were significant. According to the significant interaction effect, the team members in the control teams spent more planning ahead during non-targets compared to targets, $M_{\mathrm{ContNonTarget}} = 8.82$, $SD_{\mathrm{ContNonTarget}} = 11.2$, $M_{\mathrm{ContTarget}} = 3.52$, $SD_{\mathrm{ContTarget}} = 4.12$, $p < .05$. Also, the control teams did more planning ahead than the synthetic teams for non-targets, $M_{\mathrm{SynNonTarget}} = 5.39$, $SD_{\mathrm{SynNonTarget}} = 4.58$, $p < .05$. This conditional difference was not seen for the targets, $M_{\mathrm{ContTarget}} = 3.52$, $SD_{\mathrm{ContTarget}} = 4.12$, $M_{\mathrm{SynTarget}} = 5.34$, $SD_{\mathrm{SynTarget}} = 5.14$, $p < .05$. In the synthetic condition, team members did the same amount of planning ahead in both of the situations, non-target and target, $p = .98$. Additionally, the significant target main effect shows that planning information was mostly given during non-targets, $M_{\mathrm{NonTarget}} = 7.02$, $SD_{\mathrm{NonTarget}} = 6.53$, $M_{Target} = 4.47$, $SD_{Target} = 7.08$, $p < .05$. Overall, these results show that the control teams planned more during non-targets than during targets.

Overall results for *planning ahead* indicates that the teams in the control condition conducted more planning. Even if the marginal amount of planning ahead behaviors were equal for both conditions, the amounts for each situation were different. Due to *planning ahead* being part of pushing information, this interaction could be related with the fact that the relationship between pushing information and TPE were different in each condition (discussed in the following section).

## *C. Growth Curve Modelling Results*

Growth curve modelling was used to analyze TPE over the five missions. Overall TPE was modeled by a quadratic growth model with fixed effects of Determinism (DET) and also pushing and pulling information variables in a quadratic time term. For the final model, statistical significance ($p$-values) for individual parameter estimates was assessed using the normal approximation. During the model building steps, we used team as a random variable (as a grouping variable), determinism, pushing and pulling information were used as Level 1 variables, and finally, condition was used as a Level 2 variable.

Model 0 (random intercept model) represents a null model. In order to find how much TPE variation is present at the condition level, we calculated Intraclass Correlation (ICC) from the null model. The ICC finding (0.23) indicates that variation in the effect means (level-2) accounts for 23% of the total variability in the TPE, and therefore, we continue with Multilevel Modelling (MLM) due to the substantial amount of level-2 variability [55]. Also, we used team as a random, group variable.

In Model 1, first, linear time was added as a predictor of TPE, and then tested. In Model 2, quadratic time was added, and tested. The findings indicate that while linear time did not improve model fit ($\chi^2$ (1) $= 0.58$, $p = .45$), quadratic time did improve model fit ($\chi^2$ (1) $= 10.3$, $p < .05$). Thus, we retained the quadratic time term during the rest of the model building steps. In Model 3, level-1 variables, the effect of Determinism (DET), pushing and pulling information, were included to the best fitting model, and they did not improve model fit (Model 2 – Model 3 comparisons: $\chi^2$ (3) $= 5.87$, $p = .12$). After that, in Model 4, we also added quadratic time as a random slope and tested, and it improved model fit based on the previous model ($\chi^2$ (5) $= 25.6$, $p < .001$). Therefore, we continue model building steps with random intercept and random slope with quadratic time. After that the level-1 variable interaction effect with quadratic time was added in the model, but it did not

TABLE IV
RESULTS OF MODEL TESTS FOR TARGET PROCESSING EFFICIENCY

| *Models* | *# of parameter* | *Log Likelihood* | *Deviance* | $\chi^2$ | $\chi^2$ *df* | *p* |
|---|---|---|---|---|---|---|
| Model 0 | 3 | -675.40 | 1350.8 | | | |
| Model 1 | 4 | -675.11 | 1350.2 | 0.58 | 1 | 0.446 |
| Model 2 | 5 | -669.94 | 1339.9 | 10.34 | 1 | 0.001 |
| Model 3 | 8 | -667.01 | 1334.0 | 5.87 | 3 | 0.118 |
| Model 4 | 13 | -654.19 | 1308.4 | 25.64 | 5 | 0.000 |
| Model 5 | 14 | -653.92 | 1307.8 | 0.53 | 1 | 0.465 |
| Model 6 | 17 | -649.01 | 1298.0 | 9.83 | 3 | 0.020 |

TABLE V
RESULTS OF MODEL TESTS FOR PREDICTING TARGET PROCESSING EFFICIENCY BY DETERMINISM, PUSHING AND PULLING INFORMATION

| *Fixed effects* | *β* | *SE* | *t* | *p* |
|---|---|---|---|---|
| Initial status ($\beta_{0i}$) | | | | |
| Intercept ($\gamma_{00}$) | 863.30 | 30.22 | 28.56 | 0.000 |
| DET. in Control ($\gamma_{30}$) | -4.69 | 0.68 | -6.89 | 0.000 |
| Push in Control ($\gamma_{40}$) | 1.23 | 0.50 | 2.45 | 0.020 |
| Pull in Control ($\gamma_{50}$) | 1.99 | 1.22 | 1.63 | 0.115 |
| Synthetic (Syn.) ($\gamma_{01}$) | -37.84 | 26.26 | -1.44 | 0.170 |
| DET. in Syn. ($\gamma_{31}$) | -10.24 | 1.75 | -5.86 | 0.000 |
| Push in Syn. ($\gamma_{41}$) | -0.54 | 0.46 | -1.18 | 0.248 |
| Pull in Syn. ($\gamma_{51}$) | -0.77 | 1.81 | -0.42 | 0.683 |
| Rate of Change ($\beta_{1i}$) | | | | |
| Time (linear) ($\gamma_{10}$) | 45.36 | 21.14 | 28.56 | 0.046 |
| Time (quadratic) ($\gamma_{20}$) | -99.75 | 39.54 | -2.52 | 0.021 |

improve model fit, $\chi^2$ (6) $= 11.2, p = .08$. Therefore, we did not include this interaction effect in the model building steps, but we retained the main effects to investigate potential interactions with the level-2 variable, condition.

In Model 5, the level-2 variable, condition, was added in the model, and it did not improve model fit compared to Model 4, $\chi^2$ (1) $= 0.53$, $p = .47$. The interaction effect of condition and quadratic time was added in the model, but it also did not improve model fit based on Model 5, $\chi^2$ (2) $= 1.71, p = .43$. Thus, we kept the condition effect in the model building steps to see its interaction with level 1 variables, but we excluded its interaction effect with quadratic time.

In Model 6, we added interaction effects of condition with the level-1 variables (DET, pushing and pulling information), and these interactions did improve model fit compared to Model 5, $\chi^2$ (3) $=$ 9,83, $p < .02$. The test statistics of Model 6 are summarized in this study, however, we have still provided fixed effect parameter estimates and their standard errors with *p*-values estimated using normal approximation for the *t*-values for each model during the step by step model development process in Table IV.

In Model 6, initial status was significantly different from zero ($\gamma_{00} = 863$, $SE = 30.2$, $p < .001$) which may indicate that participants already had structured communication due to the training before starting the task. The rate of change, i.e., slope, for linear and quadratic time were significantly positive ($\gamma_{10} = 45.4$, $SE = 21.1$, $p < .05$) and negative ($\gamma_{20} = -99.8$, $SE = 39.5$, $p < .05$), respectively. The quadratic time indicates that TPE decreased over time, likely due to high workload of the last mission. The last mission had more target waypoints and more roadblocks (previously embedded target waypoints) than the other missions in order to increase sensitivity to differences between the high-performing and low-performing teams. In this model, the synthetic condition also performed more poorly than the control teams ($\gamma_{01} = -37.8$, $SE = 26.3$, $p = .17$).

The main effect of DET, for both conditions, was negative on the initial status of TPE ($\gamma_{30} = -4.69$, $SE = 0.68$, $p < .001$; ($\gamma_{31} = -10.2$, $SE = 1.75$, $p < .001$) in Model 6 (See Table V). In this case, the relationship between DET and TPE was negative for the control condition but roughly twice as negative in the synthetic condition. Thus, it seems that the belief that one team member is a synthetic agent can intensify the effect of DET on performance.

In Model 6, while pulling information was unrelated to TPE in either condition (see Table V), pushing information was positively related with TPE in control teams, $\gamma_{40} = 1.23$, $SE = 0.50$, $p < .05$, but negatively related to it (though, not statistically significant) in synthetic teams, $\gamma_{\mathrm{SynPush}} = -0.54$, $SE = 0.46$, $p = .25$. Because "pushing" information is comprised of three team verbal behaviors, this difference in relationship with TPE across conditions may be due to differences in the frequencies of each individual behavior across conditions. For instance, based on the ANOVA results for the team verbal behaviors, the control teams did more planning (i.e., the teams were more active) during encounters with non-targets than the synthetic teams. On the other hand, "suggestions" were found to be more common in synthetic teams and this was associated with worse TPE [47]. Thus, being more active and planning before the targets helped the control teams to increase their performance (positive relationship with the TPE and would lessen the need for "suggestions").

## V. DISCUSSION AND CONCLUSION

In the current study, we focused on complex adaptive team behavior by considering team interaction patterns and team communication behaviors and their relationship with Target Processing Efficiency (TPE) within the context of "synthetic" and all-human teams. The primary findings from this study are: (1) control teams demonstrated better TPE than the synthetic teams; (2) control teams were more active than the synthetic teams in terms of planning the task (which is part of pushing information), and (3) the behavioral passiveness of the synthetic teams (due to lack of planning) may have resulted in reduced overall complex behavior and diminished TPE.

During the task, any participant who filled the synthetic agent role used natural language while communicating with their team members during the team task. Yet, the synthetic teams had worse TPE due to a behavioral change of the human team members. In order to better understand these changes, we closely looked at the team communication behaviors as well as team communication flow. In doing so, we found that, compared to control teams, the synthetic teams did less planning during non-target waypoints. As anticipation is part of pushing information, this indicates that the way that the synthetic teams pushed information may have adversely affected their overall ability to anticipate their teammates' needs and, by extension, their TPE.

Therefore, the synthetic teams were less adaptive compared to the control teams did, and it had a negative effect on their TPE.

Team interaction patterns and team communication behaviors are the main indicators in the present study and we used them to predict TPE. As expected, high determinism was negatively associated with TPE, because predictable team interactions are ineffective in highly dynamic and complex environments (which demand constant adaptation and resilience). Based on previous studies, more pushing information is needed for better task performance. With this study, we build on that conclusion with the finding that, specifically, it is effective task planning—part of effective team anticipation—that is needed for effective TPE in a dynamic task environment. Overall planning ahead is important for this task. However, planning is best done during non-target encounters than during target encounters, because targets demand more coordination and adaptation on the part of the team. Also, anticipation of team members' needs in the synthetic teams was unrelated to their TPE, whereas in the control teams, it was positively related. One explanation for this is that the control teams knew that the pilot was also human and, therefore, the team members could adequately anticipate their teammate's needs, as opposed to members in synthetic teams who were likely unaware of the needs of the synthetic agent or anticipated that the synthetic agent needed no help from them. In a previous study, it was found that human team members in synthetic teams exerted more control on the synthetic team member (via giving more suggestions) [47]. However, pulling information in both groups of teams was unassociated with TPE. From these findings, we have learned that flexible team interaction and effective team anticipation of team members' needs are important for effective team coordination (TPE) in a dynamic environment.

One of the most interesting overall findings of this research study is the potential negative impact that teaming with a synthetic teammate may have on team performance. As previously noted, the synthetic agents communicated using natural language and the only difference between control and synthetic teams was the manipulation in which teams were told that the pilot was either a human or a synthetic agent. This appears to be a simple manipulation, yet it clearly impacted teamwork behaviors resulting in an adverse effect on synthetic teams. In general, this finding indicates that the simple perception that a human is working with a synthetic agent for the purposes of teaming may be harmful to team dynamics and ultimately team behaviors. Therefore, the question moving forward is how to overcome this impactful perception. There are multiple strategies that may be implemented to lessen or alleviate this perception.

Generally speaking, we see two main strategies where 1) the focus is on improving interactions through the human, and 2) the focus is on improving interactions through the agent. In reality, the optimal strategy for overcoming these negative perceptions is most likely a combination of both. First, we will outline our focus on how to improve interaction through the perspective of the human. Although, humans are becoming increasingly aware of how to interact with synthetic agents (the most popular examples being Amazon Echo and Apple's Siri), we are still not well versed in interacting with agents for teaming. Humans need more experience in teaming with synthetic agents to become more adept at the specific communication behaviors outlined in this study. We recommend that future synthetic teams participate in significant training that would focus on how to communicate with the synthetic teammate and outline what its role and goals are. We expect teaming with agents to generally improve as humans gain more experience interacting with them in everyday life, but traditional teaming will most likely not occur in everyday day life, necessitating the need for training. Training is also needed for understanding how to interact with different agents in different systems. Much like humans, agents may be different, depending on their coding and algorithms, meaning that training will need to be specific to the human-autonomy team. Even though the only difference in his study was perception, it is likely that the humans needed additional experience interacting with the "agent" to develop trust and other behavioral characteristics.

Secondly, as we transition into the utilization of using real synthetic agents for teaming, we need to continue to improve the way in which the actual agent will interact with humans. The benefits of computational intelligence, specifically modeling and machine learning allow for the agents to potentially grow in their understanding of task, context, and the principles of teaming. A great deal of work is needed to improve on these dimensions, but as they begin to improve it will provide humans with experiences of interacting with real synthetic agents in a meaningful and effective way. Potentially, one of the reasons that humans had negative perceptions about working with a synthetic agent is due to their previous experiences (failures) with interacting with similar agents. As humans continue to have positive experiences with agents, we are hopeful that this negative perception will dissipate.

Additionally, we also believe that the power of computational intelligence can help in the analysis of dynamic team behaviors. Utilizing machine learning capabilities, it is possible to develop algorithms that can recognize patterns in regard to both communication and coordination of information. Using machine learning to analyze team behaviors would then become much less time consuming on the part of the human, and in some instance the analysis could be conducted in real time allowing for feedback about their communication and coordination to be provided to the team in a meaningful way.

Finally, additional research on how humans need to interact with agents for teaming is needed, as well as research focused on computationally improving social aspects of agents. Also, this study only considered non-professional teams (teams without professionals who commonly work with autonomy). In the future, it would be quite useful to study the team dynamics of professional teams in a HAT setting. More work is needed to better understand the subjective nature of how humans view and feel when teaming with a synthetic team. The work presented here certainly suggests that negative perceptions regarding a synthetic teammate can influence team performance, but future work needs to specifically capture what those perceptions are in relation to team performance. Our previous work has noted that humans don't mind working with the synthetic teammate [47] but more work is needed to better understand the relationship.

Human-autonomy teaming is the next generation of teaming and will have a significant impact on work and society moving forward. As demonstrated in this study, there are potential issues with human-autonomy teaming that have yet to be overcome.

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