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# Trust and Team Performance in Human–Autonomy Teaming

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**ABSTRACT**

This study aims to better understand trust in human–autonomy teams, finding that trust is important for team performance. A Wizard of Oz approach was used to simulate an autonomous agent team member, in a remotely piloted aircraft system research environment, to study the relationship between trust and team performance in human–autonomy teams. Results show that (1) there are lower levels of trust in the autonomous agent in low-performing teams compared with medium- or high-performing teams; (2) there is a loss of trust in the autonomous agent over time across low-, medium-, and high-performing teams; and (3) both low- and medium-performing teams indicated lower levels of trust in their human team members. These findings indicate that trust in a teammate (autonomous or human) is associated with team performance and that trust may evolve over time irrespective of team performance.

**KEY WORDS AND PHRASES**

Human–agent interaction; human–autonomy teaming; team performance; teamwork; trust

Human–machine interaction has a long history and has been studied in a multitude of research communities ranging from human factors to information science and computer science, and from multiple different focuses (communication, awareness, trust, etc.). Given the increasing pace of technological developments in recent years, our understanding of human–machine interaction is still relatively limited.

As the field of human–machine interaction has grown, it has branched out into more well-defined areas of research, most notably human–machine teaming. Broadly speaking, human–machine teaming is when a human and a machine have interdependent roles that require interaction to achieve a common goal. The machine can consist of different technologies, such as a hazard warning system, a virtual agent (e.g., Siri), a decision support system (e.g., IBM's Watson), or an embodied robot with artificial intelligence (e.g, Rethink Robotics's Baxter). In recent work, teaming is studied from the perspective of either human–machine interaction or human–autonomy teaming. The differences between these two areas tend to lie in the freedom that is given to the machine, meaning that the technology has the ability and is given the authority to make choices on its own (i.e., in human–autonomy teaming the human is not in direct or supervisory control of the machine) [40]. Although many disagree that *autonomy* is an accurate descriptor for any type of machine, no matter how capable it is [29, 32, 42, 61], we follow the practical convention of [22] and [4] and use *autonomy* to refer to machines that have the ability, and are given the authority, to make decisions and take actions on their own.

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From a team science perspective, human–autonomy teaming can be analogous to human–human teaming in so far as its team members each have their own expertise and the authority to take action. From a roles standpoint, they interact more like peers rather than as supervisors and their subordinates [1]. This difference in role structure has important implications for the way we think about and conduct research in human–machine interaction. Yet little is empirically known about human–autonomy teaming because of prior limited machine capabilities. In recent years, the advent of advanced cognitive modeling techniques [55] and artificial intelligence [36] has brought to light the possibility of machines serving as peer-like teammates and paved the way for studying human–autonomy teams. We are at an inflection point at which there is significant need to validate, translate, and possibly transfer the assumptions and findings of canonical human–human teaming characteristics, and human–machine interaction concepts, to the new paradigm of human–autonomy teaming. We need to know how human–human teams are similar and different from human–autonomy teams. There is often an assumption that these two types of teams will be similar and that human–human teaming may be an ideal model for human–autonomy teaming, but we simply do not know beyond the findings of a few early studies. These assumptions need to be tested and verified.

Team trust is one such human–human teaming characteristic that needs to be further investigated in human–autonomy teams. The concept of trust has substantial history within the domain of human–machine interaction [27, 33, 44, 51] with some preliminary work in human–autonomy teaming [7]. Compounded with the lack of research on trust in human–autonomy teams is that autonomy has increased degrees of freedom that could potentially affect trust both at an individual and team level, depending on their dynamic interactions over time and their resulting team performance. In this paper, we present a study focused on better understanding trust in human–autonomy teaming, with a specific focus on understanding the relationship between trust in an autonomous synthetic agent and team performance.

For this study, the autonomous synthetic agent, operating in the role of an autonomous team member in a remotely piloted aircraft system (RPAS), was a trained confederate human acting as an agent. Yet in other work, the agent has been built using a computational cognitive model. The use of cognitive models as teammates has been a focus of recent Adaptive Control of Thought—Rational (ACT-R) research [2]. In previous studies of human–autonomy teams, the synthetic virtual agent comprised five components: language analysis, language generation, dialog modeling, situation modeling, and agent–environment interaction [3]. Understanding how trust develops in human–autonomy teams could help refine specific elements of the model, in that feedback from the human (e.g., their trust level) is used to configure more optimal approaches for each component.

The teams presented in this study consist of three heterogenous roles working to complete a command-and-control task (i.e., team control of an RPAS). We brought teams of two into the lab and used a Wizard of Oz approach to simulate an autonomous agent as a third team member [14, 17, 18]. This method allows an experimenter to play the role of an autonomous synthetic agent teammate (communicating and coordinating information in real time to human team members) without having to actually program a synthetic teammate to fail at particular times and without the other team members realizing that it is actually a human controlling the synthetic team member.

Given the need to better understand how dynamic team interactions and team performance relate to trust in human–autonomy teams, time was the main manipulation of this study, with a focus on the following research questions:

RQ1: Is there a relationship among humans' trust in the synthetic teammate agent and overall team performance over time?

RQ2: In human–autonomy teams, are there issues of trust among humans? If so, how is that related to overall team performance over time?

RQ3: How does human trust of a synthetic teammate agent develop over time?

Throughout the experiment, in addition to having to command and control an RPAS, team members had to overcome a series of system failures relating to automation in the RPAS, failures of the synthetic teammate, or a malicious cyberattack. These failures are described in more detail in a subsequent section and were injected into the task to better understand how they impact team performance and how team trust is impacted during instances in which dynamic communication, coordination, and cooperation are needed. The paper proceeds with a background pertaining to trust and human–autonomy teaming, an overview of study and methods used in this empirical effort, results, and a discussion highlighting important findings and suggestions for moving forward.

## Study Background and Literature Review

### *Human–Autonomy Teaming*

In general, teaming permeates throughout our society, specifically within e-commerce [10, 46]. Specific technologies within e-commerce are using autonomous technology [6, 43] with an eye to implementing them in collaborative mediums. The number of autonomous machines that can function in roles typically occupied by human team members will likely increase in the years to come, particularly as work environments become more virtual. Such machines should be able to maintain appropriate trust over time, leading to higher team performance. If goals are not met, and uncertainty is high within the human–autonomy team, then research has shown that teams will perceive a higher workload and will be less able to complete multiple tasks [62]. Effective human–autonomy teaming must consider several issues, such as creating an autonomous agent that can efficiently work with humans, modeling the team interactions, and modeling human cognition to incorporate in autonomy design [25, 47]. Therefore, human–autonomy teaming research is typically grounded in the fields of computer intelligence [5, 60], cognitive science [5, 31], and team cognition [11] to create the necessary conditions and understanding for effective human–autonomy teaming. Until recently, there has been a lack of empirical human–autonomy teaming research.

McNeese and colleagues [40] recently published a study looking at multiple team characteristics in a real human–autonomy team. The human–autonomy teaming took place within a simulated RPAS, and the humans were able to chat with an autonomous agent, in real time, using restricted natural language [19]. Findings from this study highlight that human–autonomy teams performed as well as human–human teams in the same simulation, but human–autonomy teams were deficient in aspects of team-level communication and coordination. Complimentary research using this same simulation for the purposes of human–autonomy teaming has also outlined the importance of situational awareness [15] and team synchrony [16]. In addition, other work has developed a naturalistic decision-making-based cognitive agent that helps people make decisions by improving situational awareness but increases cognitive load [19]. Other research has used the Wizard of Oz approach to simulate an autonomous agent as a team player [59]. Research that tested human–autonomy teaming in a joint resource management and scheduling task also found that different cooperative strategies of a machine agent's behaviors [8] and social exchange structures [9] can impact human teaming behavior and overall team performance.

## *Trust in Human–Autonomy Teaming*

Trust is a multidimensional construct that has been investigated in different areas of research, including in interpersonal relationships [38], teams [56], and with automation [33]. Trust is often viewed as an important concept in the electronic commerce community [23, 30, 34]. A widely accepted definition of trust is "the attitude that an agent will help achieve an individual's goals in a situation characterized by uncertainty and vulnerability" [33, p. 51]. This definition, based on a review of both trust in automation and interpersonal trust, distinguishes trust as an attitude from trust as belief, intention, or behavior to help explain the influence of trust on behavior. However, this definition also relies on a framing of trust in which people are supervisors of machines, and so a person's trust depends primarily on the observable characteristics of that machine. Under more peerlike conditions, such as with human–autonomy teaming, a definition of trust that is closer to interpersonal trust may be more appropriate.

Given the lack of work on trust in human–autonomy teams, we borrow a definition from interpersonal trust in organizations, in which trust is "the extent to which a person is confident in, and willing to act on the basis of, the words, actions, and decisions of another" [38]. As previously noted, an autonomous agent used in human–autonomy teaming can come in many different forms (e.g., software agent, embodied robots) and will need to participate in developing trust within the team. Team trust could be a critical element in determining how teams will perform in situations that are suboptimal.

Specific to the study presented in this paper, our focus is on teaming under degraded and underdefined task conditions, when trust is likely to have the most observable impact on team performance. In organizations, three characteristics of an agent affect interpersonal trust [37]: ability, integrity, and benevolence. Ability is the agent's skills, competencies, and characteristics that enable individual team members to influence a specific domain. Integrity, which can be determined by the agent's policies, will have a set degree of acceptability that the agent will need to adhere to. In agent and distributed computing model contexts, the policy can be defined as "an enforceable, well-specified constraint on the performance of a machine executable action by a subject in a given situation" [4, p. 368]. Benevolence refers to the agent's intent with respect to the trustee's intent, and in teams this intent should align with the team goal.

Many factors related to trust in automation and autonomy have been investigated. Olesen and colleagues [45] outline multiple variables that can impact a human's level of trust in an autonomous teammate: (1) human influences (e.g., individual differences in personality, experience, and culture), (2) machine influences (e.g., robotic platform, robot performance in relation to automation, failure rates, and false alarms), and (3) environmental influences (e.g., task type and operational environment). Two specific areas related to human–autonomy teaming have garnered substantial attention: anthropomorphism and transparency. De Visser and colleagues [57] found that anthropomorphic cues reduced initial expectations of automation to execute flawlessly. This finding suggests that qualities such as perceived agency, intentionality, physical presence, and biological motion can elicit anthropomorphic perceptions of autonomous agents. Recent work examining how different levels of intelligent agent transparency impact trust in human–agent teaming found that trust increased as a function of transparency level, meaning that the more transparent the agent, the more trust humans had in it [41]. Scholars have also highlighted the importance of communicating intent to engender trust in human–autonomy teaming [52] and the importance of trust repair in human–autonomy teaming [58].

## Literature Review Summary

In the past decade, substantial progress has been made in understanding the factors that affect human–autonomy teaming, including how human–autonomy teams perform in a variety of contexts. In parallel, work on trust in human–machine interactions has also flourished during this time. Yet in general, additional work is needed when trust is specifically considered in the context of human–autonomy teaming. As outlined, a great deal of the trust in human–autonomy teaming work has focused on theory development, or on aspects of trust associated with specific technology features, such as anthropomorphism or transparency. Work that focuses specifically on how trust in human–autonomy teams develops through interactions over time, and how trust impacts team performance, is needed. The work presented in this paper adds new insight to these research gaps.

## Hypotheses

As just reviewed, a fair amount of theoretical work underlies how trust could and should be viewed within the dynamic context of human–autonomy teaming. Such work has identified key characteristics that may impact trust in autonomy [45]. Previous work has also sought to operationalize trust within this context, noting multiple attributes to be considered [37]. We use these prior contributions to inform our hypotheses.

H1: Teams will be able to overcome automation failures more frequently, followed by autonomy failures, and malicious attacks being overcome the least.

Human–autonomy teaming is a highly dynamic context, so it is necessary to study it in the context of failure—an inevitable component of operating in highly dynamic contexts over a long period. A crucial characteristic for high-performing teams in this context is how they overcome failure. Failures related to higher levels of autonomy should be more difficult to detect and respond to than simpler and more obvious automation failures.

H2: Human team members trust in the autonomous synthetic agent teammate will be positively related to team performance.

Presuming a level of autonomy reliability and relatively stable conditions, or the ability to repair trust in unstable conditions, trust in autonomy has the potential to increase system performance [58]. Therefore, in our simulated task environment we predict that trust and team performance are closely and positively related.

H3: Human–human trust will be positively related to team performance.

The importance of trust in human relationships [54] is possibly more impactful than overall trust, or comparative to trust in human–autonomy relationships, because trust between humans may be more symmetrical than trust in an entity that cannot "trust back" [33]. In addition, the performance benefits that are seen in studies on trust between humans in teams is robust [21].

H4: Trust in the autonomous synthetic agent teammate will increase over time.

Although trust is likely to evolve over time [49], we hypothesize that trust in an autonomous synthetic agent teammate will increase over a relatively shorter period (the duration of the experiment), after working together in a team configuration, over repeated interactions.

## Participants

Forty-four participants from a large university community were recruited and participated in the study. Two participants per team were formed (22 teams) to fulfill photographer and navigator roles, and the pilot position was filled by a well-trained experimenter who mimicked a synthetic agent in terms of communication and coordination. Participation required normal or corrected-to-normal vision and fluency in English. Participants ranged in age from 18 to 36 ($M_{age}$ = 23, $SD_{age}$ = 3.90), with 21 participants self-reporting as male and 23 as female; they were either graduate students or undergraduate students. Each team participated in two sessions of about seven hours each (with one or two weeks between the two sessions), and each individual was compensated for participation by payment of $10 USD per hour.

## Experimental Task and Procedure

This study was conducted in the Cognitive Engineering Research on Team Task (CERTT) RPAS-Synthetic Task Environment (STE) [13]. The RPAS-STE is based on the United States Air Force Predator RPAS ground control station. The RPAS-STE task requires three interdependent teammates within the RPAS team, each with a unique role relevant to the team's objective of efficiently taking good photographs of target waypoints. Further, the CERTT RPAS-STE is dynamic, and taking good photos of designated waypoints requires information to be shared among teammates in a timely manner.

**Table 1.** Experimental Sessions and Task Duration.

| Session-I (Total session with breaks ≅ 6 hours) | Session-II (Total session with breaks ≅7 hours) |
|---|---|
| 1. Consent forms (15 min) | 1. Mission 5 (40 min) |
| 2. PowerPoint (30 min) and hands on training (30 min) | 2. NASA TLX I (15 min) |
| 3. Mission 1 (40 min) | 3. Mission 6 (40 min) |
| 4. NASA TLX I (15 min) | 4. Mission 7 (40 min) |
| 5. Mission 2 (40 min) | 5. Mission 8 (40 min) |
| 6. Mission 3 (40 min) | 6. Mission 9 (40 min) |
| 7. Mission 4 (40 min) | 7. Mission 10 (40 min) |
| 8. NASA TLX II, trust, anthropomorphism, and demographics (30 min) | 8. NASA TLX II, trust, anthropomorphism, demographics, and debriefing (30 min) |
| | 9. Postcheck procedure (15 min) |

*Notes*: This table is adopted from [39]. Between two sessions, there were one- or two-week intervals. From the hands-on training through the postcheck procedure, a 15-minute break was applied after each task, and there was a half-hour lunch break. Therefore, the total approximate time for the experimental session was eight hours. min = minutes; TLX = Task Load Index.

The task was carried out over a series of 10 missions (see Table 1), wherein all interactions took place via a text-based communications system (this is how agent communication occurs with humans). A single RPAS-STE mission consists of 11–12 targets and lasts a maximum of 40 minutes. During each mission, participants are required to communicate a myriad of information across the team pertaining to RPAS location, target location, and photographing information. After signing consent forms, the participants were randomly assigned to their roles and started their role-specific training. The navigator and the photographer sat in one room (separated via partitions and no face-to-face contact), and the pilot sat in another room.

In the simulated RPAS task environment, the three roles are (see Figure 1 with each role's responsibility and simulated task on the monitors): (1) navigator—provides a dynamic

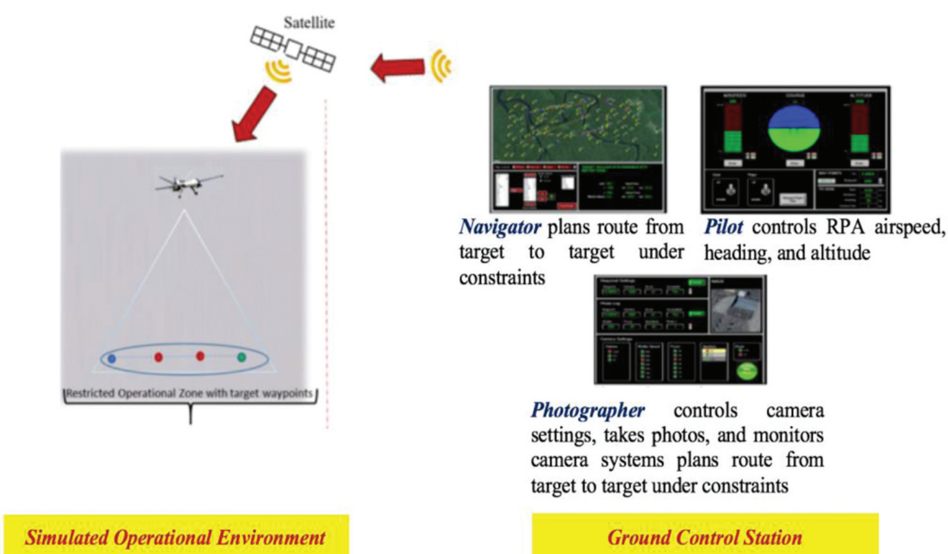


**Figure 1.** CERTT RPAS-STE Team Roles and Task. Note. The red dashed line indicates two different environments: the simulated operational environment and the ground control station. Notes: This figure is adopted from [39].

flight plan and sends the information to the pilot about the targeted altitude and the airspeed of the current target waypoint; (2) pilot—controls the remotely piloted aircraft's (RPA's) heading, altitude, and airspeed and negotiates with the photographer about the targeted speed and altitude restrictions for the current target waypoint; and (3) photographer—monitors sensor equipment, negotiates with the pilot, takes photographs of target waypoints, and sends feedback regarding whether the team took a good photograph.

## Experimental Design

In this study, the navigator and the photographer were informed that the pilot was a synthetic agent. Unknown to participants, the synthetic agent was a well-trained researcher. In this case, the "synthetic agent" pilot communicated and coordinated with the navigator and the photographer in a timely manner but with restricted vocabulary. The vocabulary used by the "synthetic agent" pilot was similar to the vocabulary used by a real-synthetic agent that served as a pilot during a previous experiment [19]. During the training and the task, the navigator and the photographer used shorthand sheets provided to them by the researchers to communicate effectively with the synthetic agent via text chat. The main manipulation in this experiment was imposing a series of failures or anomalies into the team task that fall within the three categories of automation failure, autonomy failure, and malicious cyberattacks. These categories were chosen based on pilot tests and represent different levels of team interaction mechanisms needed to recover from the failure. When automation failures were applied on the participant's task consoles, all three team members interacted to recover from the failure. For the autonomy failure, only two team members interacted to recover from the failure, because the autonomous agent failed during that time. Malicious cyberattacks overlap with both automation and autonomy failures, requiring both types of interaction mechanisms. Each failure was applied to selected targets throughout the mission, and the teams had a specific time limit to overcome each failure. Whether the team overcame the failure or not, the mission continued.

The first category—RPAS automation failure—occurred on the pilot and photographer's shared information display. This display contained information such as the current and next waypoint information and the distance and time from the current target. Three automation failures occurred separately to specific targets [24]:

- Type I Automation Failure was applied on the photographer screen, and the failure duration was 300 seconds. The photographer cannot see current and next waypoint information, including time, distance, bearing, and course deviation to the current target.
- Type II Automation Failure was applied on the pilot screen, and the failure duration was 400 seconds. The pilot cannot see the current altitude and airspeed settings as well as entering new altitude and airspeed.
- Type III Automation Failure was applied on the pilot screen, and the failure duration was 400 seconds. This failure is more intense than the Type II failure because the pilot is not aware of the current distance, altitude, and airspeed settings; time; distance; and bearing to the target F-AREA. An example view of this failure is depicted in Figure 2. To overcome this failure, the pilot needs to effectively communicate with other team members to get the right information. For instance, if the pilot receives the course

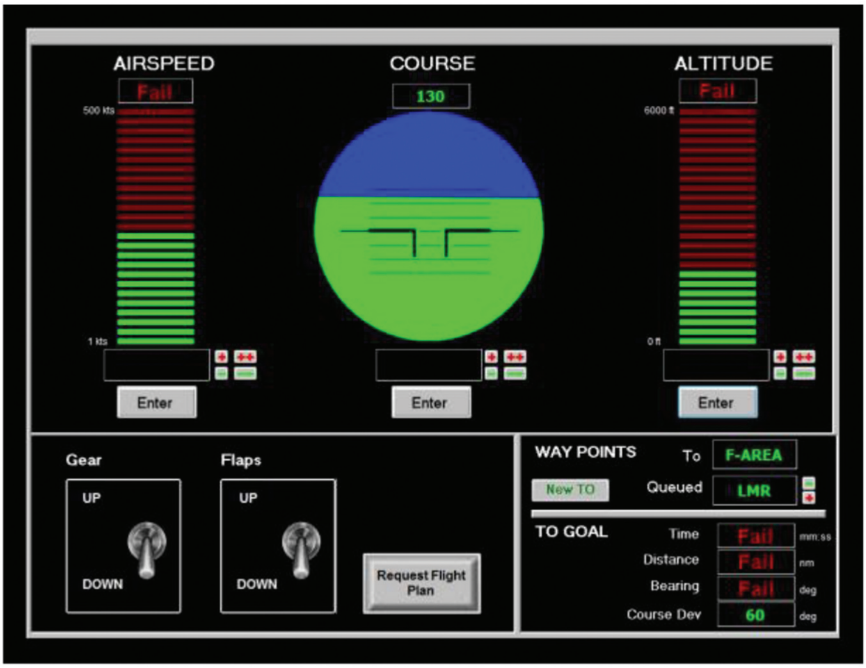


**Figure 2.** An Example View of the Pilot Screen During Type III Automation Failure.

bearing of the current waypoint from a teammate, then the pilot can adjust the current course. Likewise, if the pilot receives the current distance to the target, then the pilot can know whether it is time to take a photo.

Autonomy failures include two comprehension failures and one anticipation failure, which would arise from the synthetic teammate failing to understand a message or to anticipate (e.g., taking a good photo) the status of the team [20, 24].

*Type I Autonomy Failure* was a comprehension failure applied for 400 seconds. During the failure, the synthetic agent does not understand because of its limited verbal behavior. That is, when the human team member sends information to the synthetic agent, the synthetic agent asks the same question several times. For instance, the synthetic agent does not understand the navigator's information about the next target waypoint and continuously asks questions about it. In this case, if the navigator notices the synthetic agent's abnormal behavior, the navigator sends constructive information regarding the next target waypoint to correct it; for example, from the navigator to the pilot: "The next waypoint is K-Area. It is a target. There are no altitude and airspeed restrictions. The effective radius to take a photo is 5."

*Type II Autonomy Failure* was applied for 400 seconds, and it was an anticipation failure of the synthetic agent. During the failure, the synthetic teammate does not meet the photographer's needs to take a good photo and moves to the next waypoint without providing enough time for the photographer to take a good photo. If the phographer or the navigator notices the synthetic pilot's abnormal behavior and says, "Go back to the target waypoint!" then the synthetic agent goes back to that target waypoint to take a photo.

*Type III Autonomy Failure* was applied for 400 seconds and was a comprehension failure that would arise from the synthetic teammate failing to understand a message. During the failure, it thinks it understands a human team member but does not because of its limited verbal behaviors and language repertoire, and it performs other actions. For instance, the navigator sends altitude information to the synthetic teammate about the next target waypoint: "Altitude for next target is 3100." The synthetic teammate changes the altitude to 3100 for the current target waypoint instead of for the next target. Therefore, the synthetic pilot applies the wrong altitude during the target waypoint, and then the photographer changes the altitude for the current target waypoint. However, the pilot purposely repeats the wrong altitude several times, messaging the wrong altitude information to the photographer. If the photographer reiterates the correct information, then the pilot corrects the altitude.

Malicious cyberattacks are cyberattacks on the synthetic agent pilot, which can have the effect of flying the RPA into forbidden enemy territory while the agent denies that this is the destination. The malicious attack happened only once for each team during the final 10 minutes of Mission 10 (i.e., the last mission). If either the navigator or the photographer notices that the RPA is off-route and is going to an enemy-designated area, that individual let the experimenter know this via a chat message, and then the team has overcome the failure. During the training sessions, the experimenters highlighted enemy-designated waypoints to the navigator role, noted the importance of avoiding them, and indicated to alert intel that there is a problem if the RPA is moving toward it.

## Measures

Measures of team performance (mission and target level) and team process (process ratings, communication flow, coordination, situation awareness; i.e., number of failures overcome) and of verbal behavior were collected, in addition to measures from the human team members: facial expression, heart rate (electrocardiograms), team trust, electrical activity of the brain (electroencephalogram), NASA Task Load Index workload [26], and demographics. For this study, we consider only the following measures to address the research questions, which are presented earlier:

For *number of failures a team overcomes*, if a team successfully overcame any type of the failure by the end of a mission, then we counted 1 and took the sum across 10 missions. Therefore, we considered only the sum of the failures overcome by each team.

*Mission-level performance score* was a weighted composite score containing team-level mission parameters, including time spent in warning and alarm states, number of missed targets, and rate of good target photographs per minute (which was weighted the heaviest among the parameters). Each team began with the maximum score of 1,000 but then lost points depending on the final values of the mission parameters [12].

*Target Processing Efficiency* (TPE) score accounted for the time spent inside a target waypoint to get a good photo (higher scores equate to more efficiency; in this case, the maximum score per target is 1,000) [12].

*Team Trust* was measured via a modified questionnaire originally developed by Mayer et al. [38] to understand aspects of trust and its development. In their model, they underscore trust as an evolving process based on interactions, which accurately fits the heavily intensive interaction based task studied here [37]. In the questionnaire, we asked 25 questions with Likert-scale responses ranging from 1 (strongly agree) to 5 (strongly disagree). To assess how team trust changed across time, the questionnaire was administered twice: after Missions 4 and 10.

## Results

This first set of highlighted results address H1 (Teams will be able to overcome automation failures more frequently, followed by autonomy failures, and malicious attacks being overcome the least). The proportion of the 22 teams that overcame failures was approximately equal for both types: automation (65%) and autonomy (64%). However, the proportion of malicious attacks overcome was only 41%. We conducted a repeated measures logistic regression to ascertain the effects of type of failure and mission (as repeated measure) on the likelihood that teams overcome roadblocks. For automation failures, the tests were statistically significant for the main effects of mission, $\chi^2(7) = 22.5$, $p < 0.05$, and failure type, $\chi^2(1) = 7.20$, $p < 0.001$, but the interaction effect was not computed, because mission and failure type were perfectly correlated. The pairwise comparisons across the type of failures indicates that teams had a higher probability of failing to overcome Type III failures (failed to overcome roadblock 0 and overcoming the roadblock 1). Based on the significant mission effect, teams generally had higher probability to overcome automation failures across the missions (except Missions 3, 6, and 7; see Table 2).

For autonomy failures, the test results were statistically significant for the main effects of mission, $\chi^2(8) = 29.4$, $p < 0.001$, and failure type, $\chi^2(2) = 11.8$, $p < 0.05$, as well as for the interaction effect between mission and failure type, $\chi^2(6) = 15.7$, $p < 0.05$; this interaction was computable for autonomy failures because the failure type was not always assigned to the same mission (see Table 3). The pairwise comparisons across the type of failures indicates that teams had higher probability of failing to overcome Type III failure. Based on the significant mission effect, teams generally had higher probability to overcome autonomy failures at Mission 4 but higher probability to fail to overcome at Missions 6 and 10 (see Table 3).

Overall, H1 was partially supported. We expected teams to significantly overcome automation failures more than autonomy failures, but overcoming these failures was

**Table 2.** Longitudinal Associations between Effects of Mission and Automation Failure Type with Overcoming Automation Failure.

| | | | 95% CI | | | |
|---|---|---|---|---|---|---|
| | *B* | *SE B* | Lower | Upper | $\chi^2$ | *p* |
| Intercept | −0.06 | 0.43 | −0.90 | 0.79 | 0.02 | 0.896 |
| Type III | −11.31 | 4.21 | −19.57 | −3.05 | 7.20 | 0.007 |
| Mission 3 | 0.8 | 0.50 | −0.17 | 1.78 | 2.58 | 0.219 |
| Mission 4 | 12.34 | 4.13 | 4.26 | 20.43 | 8.95 | 0.000 |
| Mission 5 | 11.66 | 4.26 | 3.30 | 20.02 | 7.48 | 0.000 |
| Mission 6 | 0.79 | 0.70 | −0.59 | 2.17 | 1.27 | 0.334 |
| Mission 7 | 1.56 | 0.78 | 0.04 | 3.08 | 4.04 | 0.053 |
| Mission 8 | 12.13 | 4.15 | 3.99 | 20.26 | 8.54 | 0.000 |
| Mission 9 | 1.56 | 0.62 | 0.35 | 2.77 | 6.37 | 0.015 |
| Mission10 | 11.73 | 4.26 | 3.38 | 20.08 | 7.59 | 0.000 |

*Notes*: Based on pairwise tests, Type III and Type II were compared with Type I, and Missions 3–10 are compared with Mission 2. Mission 1 is omitted because it is the baseline and does not include any roadblocks. The interaction effect by type and mission is not computable because of perfect correlation. CI = confidence interval.

**Table 3.** Longitudinal Associations between Effects of Mission and Autonomy Failure Type with Overcoming Autonomy Failure.

| | | | 95% CI | | | |
|---|---|---|---|---|---|---|
| | *B* | *SE B* | Lower | Upper | | |
| Intercept | 0.509 | 0.552 | −0.573 | 1.592 | 0.851 | 0.356 |
| Type II | 1.134 | 0.877 | −0.584 | 2.853 | 1.673 | 0.196 |
| Type III | −5.618 | 1.194 | −7.958 | −3.278 | 22.147 | 0.000 |
| Mission 3 | 0.098 | 0.6535 | −1.183 | 1.379 | 0.023 | 0.881 |
| Mission 4 | 6.24 | 0.9252 | 4.427 | 8.053 | 45.49 | 0.000 |
| Mission 5 | −0.304 | 0.6799 | −1.637 | 1.028 | 0.2 | 0.655 |
| Mission 6 | −8.511 | 0.6849 | −9.853 | −7.169 | 154.412 | 0.000 |
| Mission 7 | 0.425 | 0.6678 | −0.884 | 1.734 | 0.405 | 0.524 |
| Mission 8 | 0.117 | 1.1981 | −2.232 | 2.465 | 0.009 | 0.922 |
| Mission 9 | −0.014 | 0.5033 | −1.001 | 0.972 | 0.001 | 0.977 |
| Mission 10 | −19.185 | 0.553 | −20.268 | −18.101 | 1203.504 | 0.000 |

*Notes*: Based on pairwise tests, Type III and Type II were compared with Type I, and Missions 3–10 are compared to Mission 2. Mission 1 is omitted because it is the baseline and does not include any roadblocks. CI = confidence interval.

essentially the same (automation 65%, autonomy 64%). The hypothesis is supported in that malicious attacks were overcome the least.

## Team Performance across the Missions

Because we used team score for *K-means clustering*, we reported only the mission-level scores across the 10 missions (repeated measure) and sessions. We performed a one-factor (missions) split-plot analysis of variance (ANOVA) to determine whether mission-level team scores differed over time (i.e., repeated measure of about 10 missions). The ANOVA tests of the repeated measures (i.e., mission) main effects, $F(9, 197.07) = 6.37, p < 0.001$, were statistically significant. Overall, teams demonstrated a learning effect in that team performance improved across the missions (Mission 1 to Missions 6, 7, 8 [$p < 0.05$] and 9 [$p < 0.001$]; see Figure 3).

## Target-Processing Efficiency

TPE took into account the time spent inside a target waypoint to get a good photo (higher scores equate to more efficiency). TPE was analyzed via an ANOVA, which was conducted with mission and target as within-teams variables. According to the mixed ANOVA results, there were significant mission, $F(20729) = 2.98$, $p < .001$, $\eta^2 = .38$, and target, $F(89, 1029) = 2.01$, $p < 0.001$, $\eta^2 = .15$, main effects. Accordingly, TPE score significantly increased from Mission 1 to Missions 3, 6, 7, 8, and 9 ($p < 0.05$; Figure 4a). However, TPE score fluctuated across targets because of the presence of failures (see the first four targets in Figure 4b; no improvement seen).

## Trust and Performance

The next set of results point to answering H2 (Human team members trust in the autonomous synthetic agent teammate will be positively related to team performance), H3 (Human–human trust will be positively related to team performance), and H4 (Trust in the autonomous synthetic agent teammate will increase over time).

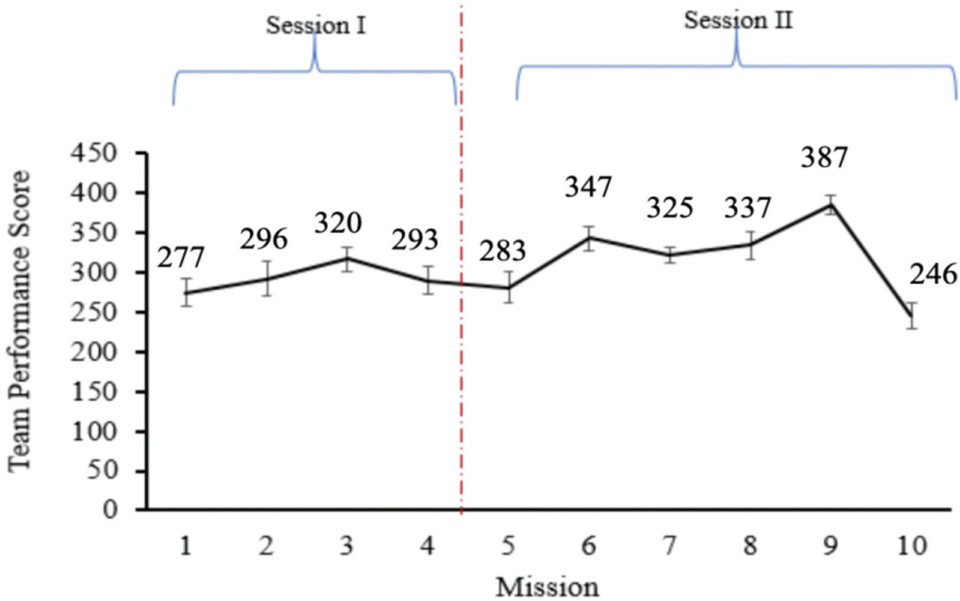


**Figure 3.** Team Performance across the Missions. Note: Vertical lines provide +/- SE.

As the relationship of performance and trust is a focal point of this study, we clustered teams into high-, medium-, and low-performing groups. By doing this, it allows for more finite statistical observations to be made across multiple levels of performance. To determine the optimal number of team clusters, we applied K-means clustering analysis on the average mission-level team performance score, target performance score, and number of failures overcome to obtain clusters. We chose this analysis technique because it minimizes the mean measure using Euclidian distance and seeks to partition the observations into a prespecified number of clusters [28]. In the clustering analysis, we excluded two teams because of the paradoxical relationship between their team score (mission and target level) and number of failures overcome (i.e., high performance but few failures overcome). The analysis was conducted using the "flexclust" 'stats' package [35] in R [48].

During the analysis, first we randomly initialized two points, called cluster centroids, and then we checked the within cluster sum of squares, which captures the amount of variability present within the clusters. However, we need to find a value of $k$ (i.e., number of cluster) that avoids overfitting the model while clustering the data close to the true empirical distribution. To solve this issue, we chose the Elbow Method, which looks at the within-groups sum of squares (wss, or equivalently the percentage of variance explained) as a function of the number of clusters [50]. According to this method, one should choose a number of clusters so that adding another cluster does not give much better modeling of the data. If the wss is obtained for multiple possible values of $k$, one can plot the wss values and find the point where the marginal drops and an "elbow" is formed (Figure 5). The Figure 5 graph shows that wss sharply drops at two clusters. It also drops with a milder slope at three clusters. Beyond three clusters, the graph levels off. Thus, we can suggest that the optimal number of clusters is three ($K = 3$; see Figure 5).

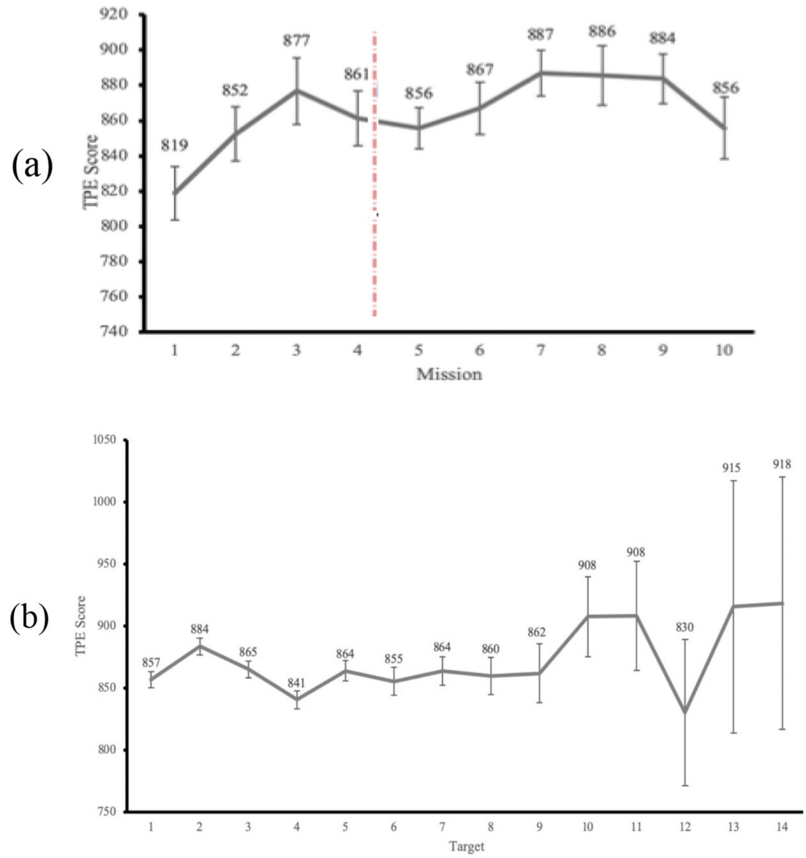


**Figure 4.** Target Processing Efficiency across (a) Missions and (b) Targets (b). Notes: Vertical lines +/- SE.

## Team Trust

To analyze team trust, we first took the average of the navigator and the photographer responses (Likert scale: 1 = strongly disagree to 5 = strongly agree) for each question. Next, we performed a 3 (condition: low-, medium-, and high-performing team) × 2 (session) × 25 (trust questions) repeated measures multivariate analysis of variance on 25 questions, for each session, and each performance cluster (condition). Results from a multivariate analysis of variance are summarized in Table 4.

Based on significant interaction effects, we also conducted pairwise comparisons (based on a least significant difference test) for each interaction, but we report only significant results from the *independent t-tests*. Turning to the significant Question × Condition effect in Table 5, we find that human team members (navigator and photographer) in low-performing teams had lower trust with one another than in high-performing teams (see Questions 1, 2, 4, 5, and 6 in Table 5). This result directly supports H3, in that lower performing teams have lower trust between the human teammates. According to Question 3, human team members in medium- and high-performing teams also trusted the synthetic agent more than in the low-performing teams. This result directly supports H2 indicating that trust in the autonomous synthetic agent teammate is positively related to team performance.

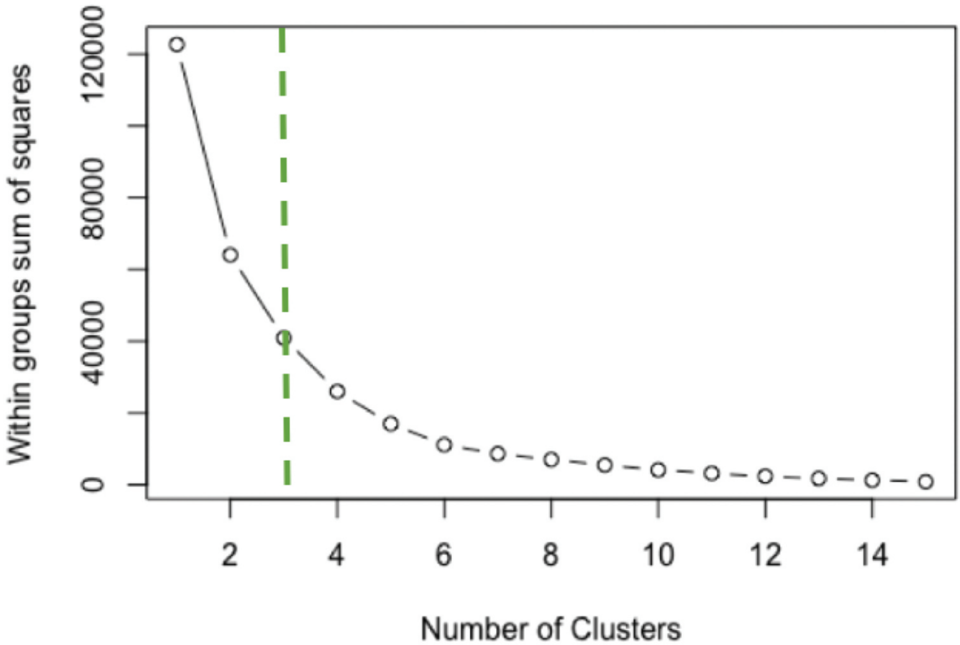


**Figure 5.** Total Within-Cluster Sum of Squares for K-Means Clustering Applied to the Average Team Performance Score, Target Performance Scores, and Number of Failures Overcome. Notes: This figure is adopted from [39].

**Table 4.** Mixed Analysis of Variance Results.

| Source | *df* | *F* | *p* | $\eta^2$ |
|---|---|---|---|---|
| Question | 24 | 14.458 | 0.000 | 0.460 |
| Condition | 2 | 0.324 | 0.715 | 0.039 |
| Session | 1 | 4.405 | 0.051 | 0.206 |
| Question × Condition | 48 | 1.791 | 0.002 | 0.174 |
| Session × Condition | 2 | 0.668 | 0.526 | 0.073 |
| Question × Session | 24 | 2.293 | 0.001 | 0.119 |
| Question × Session × Condition | 48 | 0.942 | 0.587 | 0.100 |

*Notes*: This table is adopted from [39].

According to the significant interaction effect of Question × Sessions, team members in high-performing teams increasingly viewed the synthetic agent as a machine from Session 1 to Session 2 (i.e., in response to the question "While chatting with the synthetic pilot, it felt like I was talking to a real person"; $M_{\text{Session1}} = 2.76$, $SE_{\text{Session1}} = 0.45$, $M_{\text{Session2}} = 2.34$, $SE_{\text{Session2}} = 0.50$, $p < 0.05$). Also, human team members in high-performing teams considered the synthetic agent less enjoyable (i.e., "I enjoyed working with the synthetic agent"; $M_{\text{Session1}} = 3.19$, $SE_{\text{Session1}} = 0.30$, $M_{\text{Session2}} = 2.55$, $SE_{\text{Session2}} = 0.42$, $p < 0.05$).

Based on the significant session main effect, team trust ($M_{\text{Session1}} = 3.24$, $SE_{\text{Session1}} = 0.15$, $M_{\text{Session2}} = 2.35$, $SE_{\text{Session2}} = 0.26$, $p < 0.05$) and trust in the synthetic agent ($M_{\text{Session1}} = 4.09$, $SE_{\text{Session1}} = 0.20$, $M_{\text{Session2}} = 3.54$, $SE_{\text{Session1}} = 0.25$) significantly decreased from Session 1 to

Table 5. Mean and Standard Error of Each Significant Question.

| Source | Low M (SE) | Medium M (SE) | High M (SE) |
|---|---|---|---|
| 1. If I had my way, I would not let nav./photog. have any influence over issues that are important to me. | 3.50* (0.33) | 2.88 (0.21) | 2.58* (0.27) |
| 2. I really wish I had a good way to keep an eye on the nav./photog. | 4.00* (0.29) | 3.40* (0.18) | 2.50* (0.24) |
| 3. I would tell the synthetic pilot about mistakes I have made on the team task which was critical to me, even if I could not monitor its actions. | 3.31* (0.37) | 4.35* (0.24) | 3.79 (0.31) |
| 4. I would tell nav./photog. about mistakes I have made on team task, even if they could damage my reputation. | 3.50* (0.27) | 4.30 (0.17) | 4.33* (0.22) |
| 5. I would share my opinion about sensitive issues with the nav./photog. even if my opinion were unpopular. | 3.25* (0.31) | 4.05* (0.19) | 3.83 (0.26) |
| 6. If the nav./photog. asked why a problem happened, I would speak freely even if I were partly to blame. | 3.81* (0.25) | 4.60* (0.16) | 4.125 (0.21) |

*Notes*: This table is adopted from [39]. Nav. = Navigator; photog. = photographer.
*$p < 0.05$. **$p < 0.001$.

Session 2 ($p < .05$). Probing into the significant main effect of question brought up some interesting results across individual questions. During the task, human team members trusted one another more than the synthetic agent (see Table 6). These findings do not support H4, in that trust in the autonomous synthetic agent teammate was lost over time and not gained.

## Results Overview

The summary of these findings is depicted in Table 7.

## DISCUSSION

The first finding of this study indicates that teams overcome automation and autonomy failures at about the same rate, with teams overcoming malicious attacks at a lower rate than both automation and autonomy. This finding was expected, but it is still interesting that automation and autonomy failures can be so closely related in their overcoming rate, given the current debate on the extent to which the differences between autonomy and automation are meaningful [53]. For the majority of this discussion, we focus on trust, as that is where we see the main contributions of this work.

Table 6. Mean and Standard Deviation of Each Significant Question.

| Question |
|---|
| 1. If I had my way, I would not let agent ($M = 3.56$, $SE = 0.18$) or human ($M = 2.99$, $SE = 0.16$, $p < .05$) team member have any influence over issues that are important to me. |
| 2. I would be willing to let agent ($M = 2.30$, $SE = 0.23$) or human team member ($M = 2.91$, $SE = 0.17$, $p < .05$) have complete control over my task in the team. |
| 3. I really wish I had a good way to keep an eye on the agent ($M = 4.18$, $SE = 0.15$) or human ($M = 3.30$, $SE = 0.14$, $p < .05$) team member. |
| 4. I would be comfortable giving the agent ($M = 2.67$, $SE = 0.21$) or human ($M = 3.63$, $SE = 0.14$, $p < .05$) team member a task or problem which was critical to me, even if I could not monitor his/her/its actions. |
| 5. If someone questioned the agent's ($M = 3.21$, $SE = 0.21$) or human team member's ($M = 3.76$, $SE = 0.13$, $p < .05$) motives, I would give the agent/nav./photog. the benefit of the doubt. |

*Notes*: This table is adopted from [39]. Nav. = navigator; photog. = photographer.

**Table 7.** Mean and Standard Deviation of Each Significant Question, by Performance Cluster (Low, Medium, and High).

| Research Outcomes |
|---|
| 1. Overcoming Failures |
| **Automation (65%) > Autonomy (64%) > Malicious Attacks (41%)** |
| 2. Human team members had trust issues with each other: |
| **Low = Medium > High** |
| 3. Human team members' trusted the synthetic agent: |
| **Medium > Low; High ≥ Low** |
| 4. Team members increasingly viewed the synthetic agent as a machine: Only for **High-Performing: Session 2 > Session 1** |
| 5. Trust in synthetic agent: **Session 1 > Session 2** |

This study provides further understanding of the impact an autonomous synthetic agent team member can have on trust within a mixed human–autonomy team, that trust evolves during team interactions over time, and the complex relationship between trust in different team members and team performance. In general, we can see multiple issues with trusting an autonomous agent team member, particularly in low-performing teams. More specifically, lower levels of trust in the autonomous agent were found in the low-performing teams compared with the medium- and high-performing teams. This highlights the question of whether lower levels of trust lead to lower performance, or whether lower performance leads to lower levels of trust among team members. More research is needed to further investigate this relationship, potentially by first understanding how autonomy can impact the team's interactions, and how those interactions may then affect the team's trust.

The second interesting finding from this study is the loss of trust across low-, medium-, and high-performing teams from Session 1 to 2. The results indicate that there was more trust in the autonomous agent at the beginning of the teamwork process than at the end of the process. The question becomes, Why? One potential explanation for this is a compounding effect that human team members experienced with the agent during Session 1 (negative based on data) that bled into Session 2. In short, experiencing failures with an agent will lower trust over time, regardless of the team's final performance, given that the agent that does not engage directly in trust repair—the agent correcting its error is an insufficient trust repair strategy.

Finally, an interesting result of the interpersonal trust survey is that both low- and medium-performing teams indicated lower levels of trust in their human team members, in addition to indicating low levels of trust in the autonomous agent. For example, the question "I really wish I had a good way to keep an eye on the mission planner (human role)" was found to be significant in both low- and medium-performing teams. This indicates that trust between human team members may be more impactful than trust in autonomy, particularly in low- and medium-performing teams. High-performing teams are not exhibiting the same issues of human–human trust.

This finding also highlights a difference of the high-performing teams compared with the low- and medium-performing teams. For some reason, high-performing teams did not indicate having trust issues between human teammates (compared with the low- and medium-performing teams). A deeper exploration is needed to understand whether high team trust is what led to higher team performance, or whether higher performing teams simply rate their teammates more positively because of their perceived (and real) ability to recover from failures as a team.

Future studies should investigate whether it is the manner in which the autonomous agent interacts with human team members (communication, coordination, cooperation), or whether there is a general bias based on features that positively or negatively impacts trust in this context, irrespective of these different interaction strategies. We also recommend that future studies provide a qualitative component of their data collection, allowing human participants to openly express in their own words issues that stem from trust and additional social behavior characteristics. For example, such data could help clarify whether people associated the failures with the actual behavior of the agent, or whether they were associated with something else and generally perceived differently (e.g., not as failures but as something more inevitable).

This research has several practical implications as well. First, there is a need to develop autonomous teammates that can engender trust from humans, as it is clear that trust has an impact on human–autonomy team performance. This could mean that behaviors associated with trust would need to be computationally coded and implemented within real-world human–autonomy teaming environments. In addition, developing trust in human–autonomy teams cannot only be focused on human–agent team members, because trust between the human team members may impact overall team trust. Finally, additional research is needed focused on how trust in an autonomous synthetic teammate can first be developed but then maintained over time.

Our study comes with limitations that are important to highlight. First, though aspects of this study are generalizable, there is no denying that the teams studied and the tasks they completed took place in a specific simulation test bed. We encourage additional work that takes our research questions and hypotheses and tests them in different contexts. In addition, whereas the synthetic teammate in this work represents autonomy, it is not classically defined as artificial intelligence that is constantly learning on its own. Therefore, future iterations of this work that incorporate more intelligent agents would be welcomed.

## CONCLUSION

This work contributes to the trust in human–autonomy teaming literature by providing an empirical investigation of trust and team performance and trust in an autonomous synthetic teammate over time. These findings indicate that trust in an autonomous synthetic teammate and humans are both related to trust, and that trust may evolve over time irrespective of team performance.

As human–autonomy teams become more prevalent, there is a significant need to better understand the novel factors that can influence their performance. A multitude of interesting questions stem from this study and need to be further studied, such as the following: (1) Is high trust always associated with high team performance? (2) Why do lower performing teams have lower levels of trust in an autonomous agent? (3) What causes human team members to lose trust in an autonomous teammate over time? Future studies should focus specifically on how trust is gained or lost in human–autonomy teams, through more granular and qualitative analysis of team process data. Further understanding the development of trust will help to better design human–autonomy teams and inform and build the autonomous agent to account for the concept of trust.

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