An Empirical Exploration of Resilience in Human-Autonomy Teams Operating Remotely Piloted Aircraft Systems

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An Empirical Exploration of Resilience in Human-Autonomy Teams Operating Remotely Piloted Aircraft Systems

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Team resilience is an interactive and dynamic process that develops over time while maintaining team performance. This study aims to empirically investigate resilience of human-autonomy teams by examining team interaction during novel events. Team resilience is measured based on achievement of new goals during two target-specific and time-restricted failures: automation failures- role-level display failures, and autonomy failures- autonomous agent's abnormal behavior. We found that teams were more resilient during automation failure and progressed toward targets more successfully than during autonomy failures. For automation failures, at least one team member effectively interacted with other teammates in order to overcome them. However, autonomy failures took more time for human teammates to identify the failure, because the autonomous agent's abnormal behavior was not straight forward. It is possible that human teammates overtrusted to the synthetic agent and lack confidence in themselves and let the failure go on.

Introduction

Human-autonomy teams (HAT)s are complex sociotechnical systems consisting of both human and autonomous agents (Schulte, Donath, & Lange, 2016), effectively interacting and synchronizing with each other to complete a common goal or task (Demir, Cooke, & Amazeen, 2018). As a system, HATs may exhibit re-organization, emergence, and learning related to their interaction with the task environment, especially in response to novel conditions. In this case, HATs must be able to be flexible in order to remain effective in such conditions. That is, they should be both adaptive to unexpected events that adversely impact the team's ability to meet its tasks and resilient, which leads to more successful achievement of team tasks (Edson, 2012).

Based on the ideas from safety and risk management, system's resilience is the adjustment of its functioning to maintain its dependability during changing conditions (Hollnagel, Pariès, Woods, & Wreathall, 2010; Laprie, 2008). Therefore, there are two key aspects resilience that need to be considered: (1) changes which occurs in the system (human and technological factors); and (2) persistency of the system – the fact that resilience needs to be actively maintained over time (Werfs & Baxter, 2013). The changes can be categorized according to the task: goal, time frame, and environment (Ignatiadis & Nandhakumar, 2007).

An individual who is resilient is able to withstand changes within the environment—difficulties, pressures, or stressors—and recover more quickly than someone who is rigid. It is not true, however, that two resilient team members necessarily result in a resilient team (Edson, 2012). In compromised circumstances, even highly resilient teams of individuals may struggle. Examples could include technological failures (e.g., automation and autonomy failures) and complex and dynamic environmental challenges accompanied by limitations of cognitive processes, such as team interaction (i.e. communication and coordination; (Grimm, Demir, Gorman, & Cooke, 2018). As such, resilience at the team level is an interactive and dynamic process that develops over time while maintaining team performance (Alliger et al., 2015; Morgan, Fletcher, & Sarkar, 2017). A team is considered resilient if it responds to an adverse event in a timely manner (requiring effective coordination), adapts to an unexpected event rapidly and effectively, shows few stress reactions after said event, and subsequently learns from the experiences in order to maintain performance (Pollock, Paton, Smith, & Violanti, 2003). During adverse events, teams that are highly resilient, resolve internal or external challenges as effectively as possible, maintain their performance, recover quickly, and show on-going viability or the ability to handle future novel events (Alliger et al., 2015). However, in the context of human-autonomy teaming, in previous studies in which an autonomous agent was added as a team member, teams became less adaptive during the novel events due to excessive rigidity and lack of flexibility (Demir, Likens, Cooke, Amazeen, & McNeese, 2018), and in turn, they were less resilient (Grimm, Demir, Gorman, & Cooke, 2018).

The approach used in the current study to measure systems-level resilience was developed by Hoffman & Hancock (2017). In their conceptual study, resilience was considered to be a key feature of success in emerging complex sociotechnical systems and in our case that is applied to HATs. They conceptualize a resilience measure dynamically via several components, such as the time it took the system to recognize and characterize anomalies and the time it took to specify and achieve new goals. In their conceptual framework, there were two main sub-events which expressed resilience via time-based measures: (1) time taken to design a new process and (2) time required to implement it (Hoffman & Hancock, 2017).

This current study aims to empirically investigate these two sub-events as an indicator/measure of resilience in a Remotely Piloted Aircraft System (RPAS) simulated task environment by examining team interaction during novel events. To that end, we first review and describe the experimental design and applied novel conditions, or failures. Next, we formulize two sub-event phases in the RPAS task context, and then, we introduce empirical evidence of resilience and discussion about those findings.

Current Study

The current study is part of the large synthetic teammate project (Ball et al., 2010; Myers et al., 2018), which focuses on the development of an ACT-R based, fully fledged synthetic teammate, by using a human team member (either limited or human-equaled communication capability) as a synthetic agent in a Wizard of Oz Paradigm (WoZ; Riek, 2012). The current study brings a systems resilience approach from (Hoffman & Hancock, 2017) study to evaluate team resiliency during novel events or failures (i.e., automation and autonomy).

The Cognitive Engineering Research on Team Tasks RPAS Synthetic Task Environment (CERTT-RPAS-STE), which was comprised of three task-role consoles and four experimenter consoles for communication between participants via text chat, was utilized for the purpose of similuating aspects of RPAS operations related to teamwork (Cooke & Shope, 2004). The objective in the RPAS task environment was to take photographs of color-coded strategic target waypoints. Three individual, yet interdependent, team members cooperated to accomplish this goal: (1) a navigator, who created a dynamic flight plan and notified the pilot of information regarding the waypoints, including name, altitude, airspeed, and effective radius; (2) a pilot, who controlled and monitored the altitude of the RPA's, airspeed, effective radius of the current waypoint, fuel, gears and flaps, and also interacted with the photographer to negotiate regarding altitude and airspeed in order to obtain a good photograph of the target waypoint; and (3) a photographer, who monitored and adjusted camera settings to take target photos then sent feedback to the other teammates regarding photo quality.

This study followed the WoZ paradigm wherein the navigator and photographer were seated together in one room and were told that the pilot was a synthetic agent. In actuality, the pilot was a well-trained experimenter who was working from a separate room. The 'synthetic' pilot, who used restricted vocabulary to simulate that of a computer, interacted with the others in a timely manner, similar to the ACT-R based synthetic pilot in a previous experiment; see (Demir et al., 2015). Due to the 'synthetic' pilot's limited language capabilities, cheat sheets were provided to the navigator and photographer to be used during the training and task to assist in effective communication with the synthetic agent.

The current task is comprised of ten 40-minute missions. The main manipulation consists of three degraded conditions: (1) automation failure - role-level display failures while processing specific targets, (2) autonomy failure - autonomous agent behaves abnormally while processing specific targets (i.e., it provides misinformation to other team members or demonstrates incorrect action), and (3) malicious cyber-attacks - the hijacking of the synthetic agent (and in turn, RPA), which leads to the synthetic agent providing false detrimental information to the team (Grimm et al., 2018). Because the malicious cyber-attack only occurred once (during the final mission), we will focus on the automation and autonomy failures for this study. Each failure was imposed at a selected target waypoint and the teams had to find a solution in a limited amount of time. The time limit for each failure was related to the difficulty of the failure

Methodology

Participants. Twenty-two teams (44 participants) were recruited for participation from a Southwestern University as well as surrounding areas; all teams completed the experiment. Two participants per team were recruited for the photographer and the navigator roles, and the pilot position was filled by a non-participant, i.e., 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 males and 23 females. The teams were composed of undergraduate and graduate students. Each team participated in two seven-hour sessions and each individual was compensated for participation by payment of $10 per hour.

Experimental Process. We tested 22 teams in a series of ten missions, each 40 minutes long, in the CERTT-RPAS-STE. In this study, the navigator and the photographer were informed that the pilot was a synthetic agent (i.e. WoZ paradigm). However, the synthetic agent was a well-trained experimenter. In this case, one 'synthetic' pilot communicated and coordinated with the navigator and the photographer in a timely manner, but with restricted vocabulary. During the task, the vocabulary used by the "synthetic" pilot was similar to the vocabulary used by a real synthetic agent which was used as a pilot during the previous experiment (Demir et al., 2015). The experiment was divided into two sessions with a one- or two-week interval in between the sessions (see Table 1). Before the task, each team took a one-hour, role-related training (half an hour of PowerPoint slides and half an hour of hands-on training). After the training, the experimenters used a checklist to see if the navigator and the photographer were comfortable with their roles. During the training and the task, the navigator and the photographer used cheat sheets to communicate effectively with the synthetic agent. Manipulations of this experiment are time (missions) and imposing a series of failures or anomalies on the system that fall within three categories, including automation failures, autonomy failures, and malicious attacks.

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) Mission1 (40 min)	3) Mission 6 (40 min),
4) NASA TLX I (15 min)	4) Mission 7 (40 min),
5) Missions 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) Post-Check Procedure (15 min)

Note. Between the two sessions, there was a one or two-week interval. From the hands-on training through the post-check procedure, a 15-minute break was applied after each task; and we gave a 30-minute lunch break. Therefore, the total approximate time for the experimental session was eight hours.

Measures. In this study, we used the following two equations from the resilience concept from Hoffman & Hancock, 2017's study:

Resilience: In the current study, we calculated team resilience via the following two equations (Hoffman & Hancock, 2017: based on each roles' message sent time (seconds) which expresses resilience in terms of the proportion of total task time (2400sec) for subevent activities. We considered these two equations because they account for systems reorganization in a different way —known in dynamical systems theory as "entropy" (Shannon, 1948). Accordingly, the first is Hoffman and Hancock's (2017) equation:

$$[(D-R)/T]\ X\ 100 \qquad (1)$$

where *"the time it takes the system to design a new process to achieve a new goal (D) minus the time it takes the system to recognize (R) that it needs to change. Then, this value is divided by the total event time (T)"* (Hoffman & Hancock, 2017, p. 576). In our RPAS context, this score is calculated for each target score when either automation or autonomy failures happened. Specifically, any team member's first communication about the failure *(D)* minus the time it takes the first response to the failure (*R*) that it needs to change. This value is then divided by the total failure time (*T*). According to the authors, a system is more efficient in changing if the time to redesign is smaller fraction of the time it took the reorganize a need to make such a change (smaller number is greater resilience).

The second formula is about how the system implements the change: *"the time it takes the work system to begin to implement (I) a new process in order to achieve a new goal. This value is then tempered by the time it took the work system to recognize (R) that it needed to change its existing goal. This product is divided by the total event time (T)"* (Hoffman & Hancock, 2017, p. 577). In our RPAS context, this score is calculated by taking time to take a target photo *minus* the time it takes for the first team member to respond to the failure and recognize (*R*) that it needs to change. Then this value is divided by the total failure time (*T*).

$$[(I-R)/T]\ X\ 100 \qquad (2)$$

Target Processing Efficiency (TPE): is a coordintation and time based performance score which is calculated for each target. These scores were calculated based on 1000 points possible at each target less the number of seconds spent in the target radius (*r*) and minus 200 penalty points for number of missed photos (*p*). Therefore, the following formula was used for each target (Cooke et al., 2007):

$$TPE = 1000 - r - (p*200) \qquad (3)$$

Results

Design Phase. To analyze resilience scores from Formula 1 (time to change for new design ~ introduced by Hoffman & Hancock (2017)), we performed a 2 (failure type: automation vs. autonomy) x 9 (mission) split-plot ANOVA. Accordingly, main effects of failure type ($F(1, 44.5)= 45.6$, $p < .001$) and mission ($F(8, 266)= 2.64$, $p < .05$) were statistically significant, but the mission by failure type interaction effect was not statistically significant ($F(8, 266)= 1.71$, $p = .097$).

Based on the condition main effect, teams were more resilient during the automation failure (more explicit failure) than the autonomy failures (Figure 1). This result is not surprising given that teams were mostly aware of automation failures. At least one team member noticed and let the other team members know about the problem during automation failure. During autonomy failure, it took more time for human team members to identify the failure, because the autonomous agent's abnormal behavior was not straight forward.

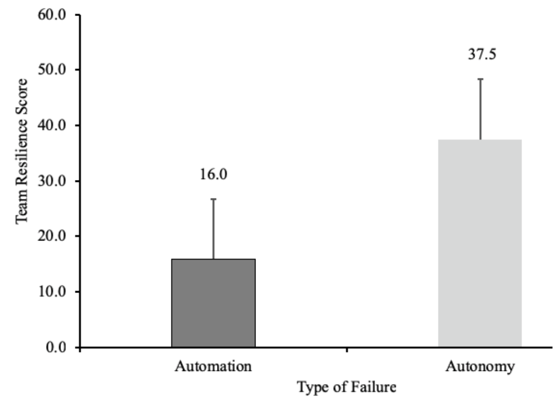

Figure 1. Resilience score for design phase across the failures (smaller score means more resilient)

Based on the mission-level main effect, teams became more resilient in both sessions (from Missions 2 to 4, and from Missions 5 to 10, $p < .05$, see Figure 2).

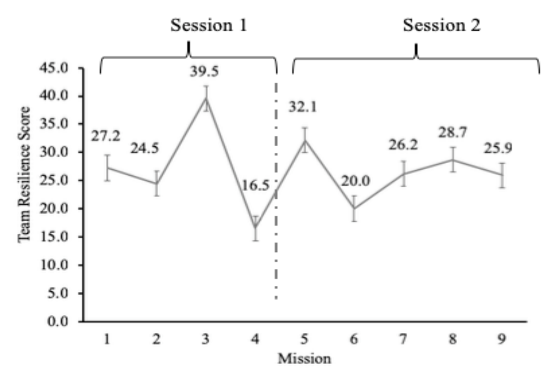

Figure 2. Team resilience score for design phase across the missions (smaller score means more resilient)

Implementation Phase. Similarly, to analyze resilience scores from the second formula (time to implement for new design ~ introduced by Hoffman & Hancock (2017)), we performed a 2 (failure type: automation vs. autonomy) x 9 (mission) split-plot ANOVA. Accordingly, the mission by failure type interaction effect was statistically significant ($F(8, 281)= 2.35$, $p < .05$); the failure type main effect was statistically significant ($F(1, 34)= 17.9$, $p < .001$), but the mission main effect was not statistically significant ($F(8, 281)= 1.76$, $p = .85$).

Based on the interaction effect, for the automation failure, team resilience was stable over time in the first session

(Missions 2 to 4, $p = .44$), but it increased in the second session from Missions 5 to 9, $p < .05$; see Figure 3. For the autonomy failure, team resiliency fluctuated over time in the first session (Missions 2 to 3, $p < .05$, Missions 3 to 4, $p < .05$) but was stable in the second session (Missions 5 to 10, $p = .71$). Taking the design and implementation phases together, teams showed better resilience during the automation failure than the autonomy failure, and it improved over time.

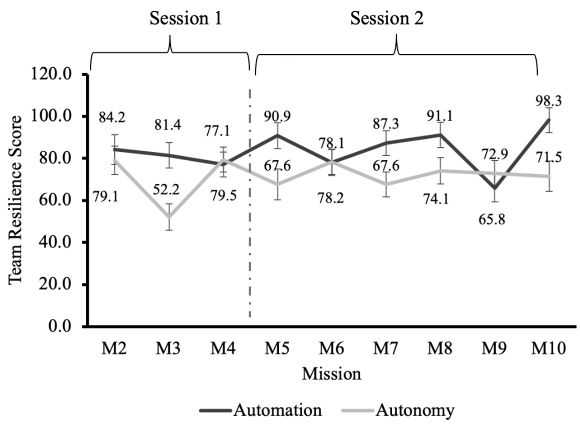

Figure 3. Team resilience score for implementation phase across the missions (smaller score means more resilient)

Target Processing Efficiency. To analyze TPE for each of targets with failures, we performed a 2 (failure type: automation vs. autonomy) x 9 (mission) split-plot ANOVA. According to the findings, the mission by failure type interaction effect was statistically significant ($F(8, 210)= 9.76, p < .001$). The mission main effect was statistically significant ($F(8, 210)= 6.36, p < .001$), but the failure type main effect was not statistically significant ($F(1, 38.9)= .99, p = .32$).

The significant interaction effect reflects the crossover pattern from Mission 5 to Mission 8 (second session): while TPE for the targets of the automation failures significantly increased, $p < .05$; for the autonomy failure, TPE significantly decreased, $p <.001$. Overall, these findings indicate that teams were more successful at overcoming automation failures than autonomy failures in the second session. Also, teams were more resilient during the automation failure than the autonomy failure. However, implementation time was longer for the automation failure than for the autonomy failure. Therefore, resilience in the implementation phase for the automation failure was lower, but it improved over time during the second session.

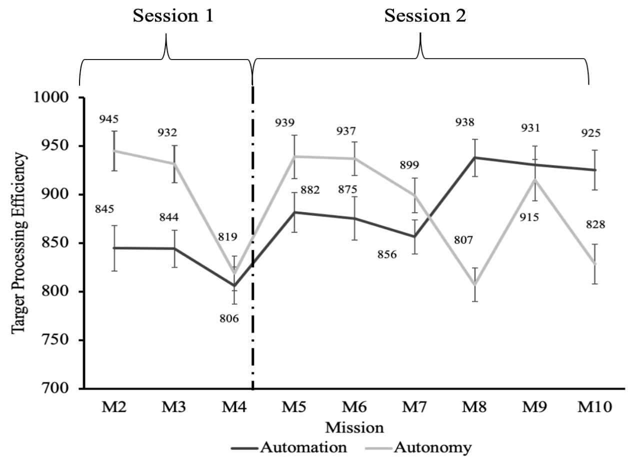

Figure 4. Target processing efficiency across the failures over time

Discussion and Conclusion

Team resilience is an interactive and dynamic process that develops over time. The current study aimed to empirically investigate resilience by considering the design and implementation of a new process through examining team interaction during automation and autonomy failures.

We found that teams were more resilient during automation failure and progressed toward targets more successfully than during autonomy failures. We see two possible explanations for this resilience: (1) automation failures are more explicit than autonomy failures, since at least one team member (potentially even the "synthetic" agent) communicated and coordinated with other team members about role-related technological failures in order to overcome it; (2) autonomy failures took more time for human team members to identify the failure, because the autonomous agent's abnormal behavior was not straight forward. In this case, it is possible that human team members (a) didin't know what to do about the autonomous agent's abnormal behavior; (b) the human teammates overtrusted to the synthetic agent and lack confidence in themselves and let the failure go on. Therefore, their resiliency may be adversely affected, and resulting in poor performance in regard to processing of the target.

In order to be adaptive and resilient in a complex and dynamic task environment, HATs should demonstrate metastable behavior (Grimm et al., 2018). To actively maintain this adaptation and resilience over time, team members (either humans or autonomous agents) interact with each other and also with their task environment in a timely manner. In this study, we only considered team members' interactions (communication flow and content) with one another during the failures, however other factors of resilience deserve further study as well. For instance, other technological factors (i.e. interaction with interface, interaction with a remotely piloted aircraft) (Grimm et al., 2018) or psychological factors (Stevens, Galloway, Lamb, Steed, & Lamb, 2015). Grimm et al. (2018) found that the automation and autonomy failures underscore that the need for a high-level of entropy, or system reorganization (with all its components) in order to be resilient, and in turn, overcome those failures. Also, Stevens et al. (2015) measured team resilience via symbolic neurodynamic fluctuations (using moving window entropy). Their findings indicate that the degree of neurodynamic organization reflected the performance dynamics of the team and that having more flexibility was important while the performing the task. Looking at technological and physiological factors in the system should be considered as a future study in the RPAS context.

When including a synthetic agent as a team member, team resilience involves another dynamic and interactive concept, team trust. Trusting an agent may or may not help teams to be resilient. In one of our exploratory studies (Grimm, Demir, Gorman, & Cooke, 2018b), we have already seen that when humans trust a synthetic agent over time, they have difficulty overcoming autonomy failures in the RPAS task context. Thus, another future area of investigation in the RPAS task context may address the relationship between resilience and trust as a predictor of team effectiveness. We hope that our findings generalize to teamwork strategies in current and future dynamic HAT domains in which social, technological, and physiological interactions are vital, or where timely responses are critical, such as urban search-and-rescue or code-blue resuscitation teams.

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