The Application of Automation Systems for Training – Implications of Trust

Emily C. Anania
Don Selvy Enterprises, Inc.
Orlando, FL
Eanania@dse-inc.net

John Killilea, Beth Atkinson
NAWCTSD
Orlando, FL
John.Killilea@navy.mil, Beth.Atkinson@navy.mil

ABSTRACT

Interactive automation has the potential to decrease the resources needed for effective aviation training systems. Currently, some training environments require instructors to monitor and train multiple individuals at once, while simultaneously acting as fellow crewmembers in the scenario. This creates high workload for instructors and decreases the efficiency of training and the quality of feedback. Leveraging automation to support instructors can reduce manpower requirements, time demands, as well as enable cost savings.

However, experience with new automated systems (positive or negative) influences instructors' trust in the technology, and therefore, future use and reliance on the system. For example, the instructor may become over-reliant on the automation and miss important aspects of the training. Conversely, they may underutilize the system, thereby increasing their workload. Trust will also influence trainees' usage of automation, altering the way each individual trainee interacts with the simulation and impacting the fidelity of the training received. This paper will expand on these potential issues, their effects on instructor and trainee behavior, and the subsequent implications for assessment of training. A protocol for measuring trust in automation within a training session will be suggested and outlined.

Lastly, the authors will provide an overview of a use-case Navy effort to develop synthetic, autonomous agents for P-8A crewmembers. The effort's technology will allow trainees to interact with simulated crewmembers, enabling instructors to focus on instruction and performance assessment. This paper will detail how potential issues with trust in automation are being addressed within this applied context.

ABOUT THE AUTHORS

Emily Anania is currently a Research Psychologist with Don Selvy Enterprises, working at the Naval Air Warfare Center Training Systems Division in the BATTLE Laboratory. She holds a Masters in Human Factors, and is currently a Doctoral Candidate in the same field at Embry-Riddle Aeronautical University.

John P. Killilea is a Research Psychologist at the Naval Air Warfare Center Training Systems Division in the BATTLE Laboratory. He holds a Masters in Modeling & Simulation, and is currently a Doctoral Candidate in the same field at the University of Central Florida.

Ms. Beth F. Wheeler Atkinson is a Senior Research Psychologist at the Naval Air Warfare Center Training Systems Division (NAWCTSD), and lead of the Basic & Applied Training & Technologies for Learning & Evaluation (BATTLE) Laboratory. She manages several Research and Development (R&D) efforts devoted to investigating capability enhancements for training and operational environments. Since 2007, she has supported several R & D efforts regarding novel technology enhancements to provide virtual role-players in individual and team training systems to optimize scenario-based training requiring a crew composition. Her research interests include instructional technologies (e.g., performance measurement, post-mission reporting/review), Human Computer Interaction (HCI)/user interface design and analysis, and aviation safety training and operations. She holds an M.A. in Psychology, Applied Experimental Concentration, from the University of West Florida.

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INTRODUCTION

As prevalent as automated technologies are in today's world, it is no surprise that training systems are becoming increasingly automated, and are integrating automated learning, feedback, and performance measures. However, the integration of automation into training systems poses many challenges, which must be addressed and understood moving forward to improve the quality of training, as well as trainee performance.

Figure 1. A P-8A Poseidon from Naval Air Station Jacksonville sits on the flightline. (U.S. Air Force photo by Senior Airman Joshua Smoot)

With the integration of automation comes the important issue of trust in automation, which must be considered not only by trainees and instructors, but by designers and decision makers who will implement these systems. Trust in automated training systems is an important topic, especially within the U.S. Navy. As automated systems come on-line and trainees have the opportunity to interact with them and learn from them, the Fleet must maintain an optimal level of readiness. As such, it is important to understand how both instructors and trainees will interact with and trust these systems that incorporate automation to address training challenges.

A long-standing training challenge that has been compounded by increased reliance on simulation-based training is how to train a single trainee in a task that typically requires a crew or group to complete. Solutions include rotating trainees (e.g., having others act as training aids for individual training), or using instructors as role-players. However, these solutions can be inefficient and costly to implement. Further, using instructors as role-players distracts from their primary objective, which is to facilitate learning through performance monitoring and providing appropriate and timely feedback. Fortunately, with recent technological advances in speech recognition and understanding, as well as advances in agent behavior modeling, the feasibility of incorporating automated synthetic role-playing crewmembers into dynamic training has increased.

Within naval aviation training, the P-8A Poseidon serves as an appropriate and willing testbed to further explore this challenge of teaming a trainee with autonomous, interactive crewmembers, making P-8A training a prime use case for investigating the effect of automation on training. The P-8A is a maritime patrol aircraft that is responsible for Anti-Submarine Warfare (ASW), Anti-Surface Warfare (ASuW), and Intelligence, Surveillance, and Reconnaissance (ISR) missions. The crew, flying in a modified Boeing 737, includes two pilots, a complement of enlisted sensor operators, and two Naval Flight Officers acting as the Tactical Coordinator (TACCO) and co-Tactical Coordinator (COTAC). The TACCO leads the tactical decision making aspect of the mission. The crew, working in unison to bring the full capabilities of each of their roles to the mission, requires clear communication and coordination throughout the entirety of the mission. As crucial as this is, the specialization of each position, number of crewmembers, and need to coordinate with personnel outside the aircrew increases the importance of inter- and intra-crew communication for long duration missions.

Unfortunately, there are few opportunities or existing capabilities for inter-crew or intra-crew communication practice until practical training, either in the various training systems, or in flight. The instructor is required to role-play the various crewmembers, role-play any outside entities, drive the training scenario itself and modify it if necessary, as well as perform the role of the instructor. One instructor performs the above tasks for up to three trainees simultaneously, typically working different scenarios. The instructor's most important role of providing individualized, timely instruction and feedback is sometimes relegated to a side task as all the previously mentioned duties interfere. There is ample opportunity for increased automation and human-machine teaming in this training environment.


Figure 2. Aircrewmen assigned to VP-8 perform pre-flight procedures aboard a P-8A Poseidon (U.S. Navy photo by Mass Communication Specialist 2nd Class Clay Whaley/RELEASED)

Fortunately, automation has the potential to decrease the resources needed for effective aviation training systems. The instructor-trainee interactions described above can create high workload for instructors and decreases the efficiency of training and the quality of feedback. Leveraging automation to support instructors can reduce manpower requirements, time demands, as well as enable cost savings.

Although there are benefits of augmenting training systems with interactive automation, experience with new automated systems (positive or negative) influences instructors' trust in the technology, and therefore, future use and reliance on the system. For example, the instructor may become over-reliant on the automation and miss important aspects of the training. Conversely, they may underutilize the system, thereby increasing their workload. Trust will also influence trainees' usage of automation, altering the way each individual trainee interacts with the automation and impacting the fidelity of the training received. The following sections discuss these potential issues, their effects on instructor and trainee behavior, and the subsequent implications for assessment of training. Relevant literature concerning automated training systems and trust in automation is presented and incorporated throughout. Lastly, the authors provide an overview of a use-case Navy effort to develop synthetic, autonomous agents for P-8A crewmembers. The effort's technology will allow trainees to interact with simulated crewmembers, enabling instructors to focus on instruction and performance assessment. This paper details how potential issues with trust in automation are being addressed within this applied context, and offers a list of recommendations for other practitioners venturing into this field.

AUTOMATED TRAINING SYSTEMS

Currently, there are numerous types of training "systems," which range from paper-and-pencil learning to incredibly high-tech simulations. Few guidelines dictate the level of automation (or even technology) which should be present within a training system for optimal trainee performance and efficiency. There is frequently a push to integrate technology for technology's sake into training, as opposed to providing a clear benefit to the system and users. As the usage of automation increases in our operational systems, it also is beginning to increase in the design and development of current training systems.

The use of automation in training is not new and is increasingly necessary. The use of automated systems in actual operational environments necessitates some use of automation in training systems, where the training automation often mimics the state of operational automated systems (e.g., autopilot on a plane versus autopilot in an aircraft simulator). However, automation can also benefit instructors by assuming roles that they have previously held. For example, automation can function as an observer for performance measurement or as an instructor leading a trainee through a scenario. In addition, there is a need to train tasks concurrently with team-based competencies (e.g., leadership, communication, coordination). Systems often exist for these training paradigms, but these systems are not always integrated. Though these skills may be separate, in the operational environment they must be performed simultaneously. Therefore, there is often a benefit to practicing team-based and task-based skills at the same time. Automation can allow for these skills to be practiced concurrently by taking on certain roles of the instructor (e.g., roleplaying other trainees). The overall benefit is that automation can save money, time, and manpower. Fewer instructors are needed, fewer training sessions are needed, and less money is required to satisfy these training costs.

As innovation pushes technology further, automation is being integrated into more and more domains, including training technologies. Automation, as defined by Parasuraman and Riley (1997) is "the execution by a machine agent (usually a computer) of a function that was previously carried out by a human" (p. 231). Automation has changed work by changing the role of the human. Within the context of automation, humans have two primary tasks: monitoring the automated system, and readiness to take control of the automated system, two functions which they should act upon when the system is not operating as expected (Bainbridge, 1983; Stanton & Marsden, 1996). Therefore, automation is not replacing the human, but instead changing the function of the human within the system. Humans are still relevant and even necessary to complete maintenance and monitoring tasks, and to act as a failsafe should the automation make errors.

Automation is not all or nothing. Most automation falls somewhere within a wide, but finite continuum – common types including automation supported by a human monitor, or a simple automated aid assisting a human operator to make decisions. This is conceptually referred to in the literature as degrees of automation (DOA) or levels of automation. DOA was first conceptualized by Sheridan and Verplanck (1978) as 10 levels, ranging from no automation (full human involvement) at level one to full automation (no human involvement) at level ten. That is, at the low end of the scale – no input or assistance is offered by the computer to assist the operator and at the opposite this end of the spectrum, the highest level indicates absolute autonomy by the computer without concern for human input (Parasuraman, Sheridan, & Wickens, 2000). Additionally, in one specific system, different components of automation may fall within multiple levels. However, overall, "more" automation generally refers to higher levels of automation, and later stages of automation (Onnasch, Wickens, Li, & Manzey, 2013). It is important to note that different levels of automation may be beneficial for different types of tasks (Taylor, Reinerman-Jones, Szalma, Mouloua, & Hancock, 2013).

However, there are typically drawbacks to the introduction of automation into a system. Automation does not always function perfectly, and automation which has a particularly high error rate can be more detrimental to performance than assistive (Dixon, Wickens, & Chang, 2004). In addition, it can be difficult to understand if trainees are responding to the training or the automation – if a trainee seems to have made a mistake is it because they made an error, because the automation made an error, or because they did not understand the function of the automation in training? When using complex systems to train, especially those involving some level of automation, these types of queries must be considered.

Drawbacks aside, the potential benefits to appropriately incorporating automation into training systems are extensive. Former Deputy Secretary of Defense, Robert Work, discussed this and other human-machine teaming issues much during his tenure. He noted that finding the right mix of automation and humans, in both training and operational systems, is considered the heart of the Department of Defense's high-tech Third Offset Strategy. This approach recognizes that although potential adversaries (and allies) can copy the U.S.'s technology, they cannot copy our people, and even less so, the relationship that the personnel have with the technology. Strengthening the bond between humans and autonomous, intelligent machine partners, and developing appropriate trust between them, is a key aspect to maintaining a competitive advantage.

TRUST IN AUTOMATION

As technology develops, it is not always warmly welcomed and trusted. There are many barriers to adoption of automated technologies; one of these key barriers is trust, or a lack thereof. Trust in automation is important to understand because it will, in part, dictate how users interact with automation. Parasuraman and Riley (1997) discuss this effect, and name one of the major implications of over-trust or under-trust as the level of automation usage by the human operator. If the operator mistrusts the system for whatever reason, they are much less likely to use it or rely on it. Indeed, there have been reports of operators taping over or disabling automated aids. A primary reason users disuse automation has to do with the automation's false alarm rate – or – how often does it indicate a problem when there really is no problem. In this scenario, the operator will likely change their opinion of the system as they are required to attend to nonexistent problems. In contrast, over-trust of a system may result in over-reliance on a system which may not be reliable – the operator may use the automation even when inappropriate or unnecessary (Parasuraman & Riley, 1997). This may result in monitoring inefficiencies, where operators do not notice failures when they are present; though countermeasures can be provided to address this issue, low detection rates are important for understanding individuals' responses to automation (Parasuraman, Mouloua, & Molloy, 1996). Either way, trust will influence the operator's reliance on automation and has important implications for not only understanding human interactions with technology, but also the design of such systems (Dzindolet, Peterson, Pomranky, Pierce, & Beck, 2003; Lee & See, 2004).

Highly-reliable automation has been shown to improve human operator performance (Dixon, Wickens, & Chang, 2004; Dixon, Wickens, & McCarley, 2007). However, automation in practice is not always reliable. Imperfect automation has been shown to degrade performance, in some instances making operators perform more poorly than had they not had an automated aid (Dixon, Wickens, & Chang, 2004). However, situational factors, such as workload, also contribute to trust in automation, and following this, the benefit of automation. Wickens and Dixon (2007) note that the performance benefits of automation are likely influenced by both the reliability of the aid, as well as the level of workload that the operator is experiencing. Predictably, the more reliable the automation is, the greater the performance benefits. Additionally, the higher the workload the operator is experiencing, the better the performance benefits are. So, in a high workload scenario, the operator will find more benefit of automation because it can more or less share some of the workload; in low workload conditions, this may not be as important. Wickens and Dixon (2007) also found that operator performance using an automated aid was more affected by the reliability of the aid in high workload conditions. There seems to be a threshold at approximately 70% reliability, such that automated aids with a reliability level over this threshold will improve performance over a baseline condition with no automation, and automated aids with a reliability below this threshold may degrade performance below baseline (Dixon & Wickens, 2006; Wickens & Dixon, 2007). In addition, the type of error the automation makes – fails to detect an error, or makes a false alarm – differentially effects how the operator will respond to the system in the future (Dixon, Wickens, & McCarley, 2006).

Trust in automation also depends on factors of the individual utilizing the automated technology, aside from both situational factors and attributes of the automation itself. Hoffman, Johnson, Bradshaw, and Underbrink (2013) note that trust in automation functions rather similar to interpersonal trust (or human-human trust), such that trust can be gained, lost, and repaired, and a number of similar factors will weigh in the decision to trust a human or a machine. However, technology's capability is limited in the sense of both performance and communication, and as such fundamentally influences trust (Hoffman et al., 2013). In addition, trust is perhaps more quickly lost in machines or automation than in humans, showing degraded trust resilience (de Visser et al., 2012). There is evidence showing that not only do individuals have differing levels of propensity to trust in automation, but also that factors such as age (Hitt, Mouloua, & Vincenzi, 1999; Pak, Rovira, McLaughlin, & Baldwin, 2016), extraversion (Merritt & Ilgen, 2008), mood (Stokes, Lyons, Littlejohn, Natarian, Case, & Speranza, 2010), gender and personality (Hoff & Bashir, 2015), and self-confidence (Lee & Moray, 1994) may influence trust in automation.

In addition, users may be resistant to adoption of a new technology dependent on their previous experiences with a system, or history of utilizing a certain system, not even taking into consideration the actual attributes of the system. As training systems change in the U. S. Navy, getting users to "buy in" to new systems is a challenge. This may be influenced by the individual, but also the culture of the organization in which the system is being implemented. However, it is important to note that in a meta-analytic review, Hancock, Billings, Schaefer, Chen, de Visser, and Parasuraman (2011) found more evidence that attributes of the robot influence trust than individual differences.

The literature discussed above principally indicates that a user's trust in an automated system is based on whether or not the user thinks that the system is performing as it should and being "honest" about the task. Designing an automated training system around this ideal can be complicated and a delicate balance. The authors discuss an applied case of this in the following section, and describe how using the existing literature can be translated into actionable experimental and system design elements.

TRUST IN AUTOMATION: CREW ROLE-PLAYERS ENABLED BY AUTOMATED TECHNOLOGY ENHANCEMENTS

Figure 3. A crewmember engages in individual training in a P-8A training system (U.S. Navy photo by Mass Communication Specialist 2nd Class Clay Whaley/RELEASED)

In an effort to provide increased fidelity within individual training environments, researchers have developed a software technology called Crew Role-player Enabled by Automated Technology Enhancements (CREATE). This research and development effort is focused on designing a synthetic role-playing capability that is anticipated to fill the aforementioned gap. The current scope of the effort involves the development of synthetic, interactive P-8A crewmember agents to include the Acoustic Warfare Operator (AWO), Electronic Warfare Operator (EWO), the Co-Tactical Coordinator, ordnance support personnel, and the pilots to support TACCO-centric training. As previously mentioned, the TACCO is a front-line Naval flight officer on P-8A aircraft responsible for the tactical portion of a patrol or surveillance flight mission. The TACCO has primarily a communications role as he or she serves as the nexus of mission-level information and must organize functions across the entire flight. Because of the reliance on communication, the opportunity exists to advance existing P-8A part-task training (PTT) systems to improve the current lack of inter- and intra- crew communication opportunities required for effective coordination training. Optimally, P-8A flight crews could train alongside other trainees or human role players; however, this is often a cost- and time-prohibitive route. As such, CREATE was conceived to augment the human TACCO trainee with a complement of autonomous, synthetic, crewmember agents. The agents will use speech recognition and understanding to respond to and communicate with the trainee, while also being able to respond behaviorally by taking actions requested of them.

The CREATE effort aims to remedy some of the current training issues associated with the part-task trainer sessions. As previously mentioned, one instructor typically presides over two or three TACCO trainees at a time. These trainees may or may not be training the same type of scenario, which can add to the complexity of instructing. The instructor sits at an instructor station that has six or more monitors, so that he or she can monitor what each of the trainees are doing in their respective scenarios. The instructor is responsible for running the scenarios, adjusting the scenarios as needed, role-playing all of the crewmembers, role-playing all of the non-ownship entities, while also retaining all typical instructor roles, such as providing feedback and assessing performance. One can imagine how difficult and confusing it can be to remember what was said, under which persona, to which trainee at a given time. The CREATE software will provide each trainee with the majority of their communication and coordination requirements through its automated crewmember agents, thus freeing the instructor to instruct. However, injecting an automated system into a previously human-driven environment requires certain considerations to ensure that the trainees, and the instructors trust the automated crewmembers to perform as expected. The considerations are discussed below, and recommendations for future research are provided.

Dealing with Trust: The CREATE Use Case Considerations

Teaming TACCO trainees with CREATE-based crewmembers will allow for somewhat automated interaction among members of the P-8A team. This will allow instructors to focus on other aspects of the training, as they will no longer need to assume the roles of the other crewmembers in order to simultaneously provide CRM training for the TACCO. So not only will the instructor's workload decrease overall, but they will be able to focus on performance assessment, and provide more detailed and diagnostic feedback and debriefing. In addition, these automated "members" of the crew will add training fidelity in the sense that communication protocols will be programmed, and trainees will be required to ask for and respond to certain information in a specified way. The trainees will be able to have multiple and repeated interactions with other automated agents playing the role of other P-8A crewmember positions. This will allow for concurrent training of tasks, as well as team-based skills, such as communication protocol and a shared understanding of crew member responsibilities.

However, research has shown that trust in automation is system-wide, rather than component-specific (Rice & Geels, 2010). Therefore, interaction with one "crewmember" may influence the way that the trainee interacts with the other "crewmembers." Important information to capture will include the frequency by which trainees utilize the system, both in terms of interaction and how often they rely on the automated agents to provide them with the necessary information to complete the training program. In addition, it is important to capture how often they "double check" the system's work, which would indicate that they do not trust the automation to provide them with the correct data. These types of measurements would provide an objective basis by which to measure trust in a system. Subjective measures of trust can also be utilized, such as the Checklist for Trust between People and Automation (Jian, Bisantz, & Drury, 2000) or any other survey-based method of assessing perceptions of trust.

This may also affect instructor's usage of the automated functions of the training system. How will the instructor utilize CREATE in practice, versus in theory? There is the possibility that, given some system malfunctions, the instructor will begin to monitor the system more closely, thereby increasing workload rather than decreasing it. This may be due to an unfounded distrust in the system (as discussed earlier, individual differences in propensity to trust may influence trust in automation) or due to previous mistakes the automation has made. Important measures to capture will include objective measures of trust and use – how often does the instructor interject or override the system? How closely does the instructor monitor the system, and does this decrease their performance in other aspects of instruction? In addition, subjective measures of perceived trust in the system can also be measured.

Another consideration for instructor usage of CREATE will be the instructor's CREATE user interface (UI). The interface must be designed at an appropriate level for the instructor to have enough but not too much information, in order to properly understand the function of the automation and whether or not it is performing as anticipated. As instructors are "managing" both the trainee and the system concurrently, it is important not to overburden instructors with too much information, or information which they would find unnecessary. As the system will be using speech recognition and generation, there will be pure (what exactly the recognition picked up), as well as adjusted transcripts (what the system determined the user meant) of all audio snippets. Should that transcript be available and present for the instructor, or should they only be notified if a recognition error has occurred? Questions such as these make it necessary to engage in multiple discussions with instructors using prototypes to determine the right opacity of the system's automation. The result will answer the key UI consideration question of how much information, regarding the automated agents, an instructor should see.

An important consideration for design and integration, which will influence both instructor and trainee interaction with the system is the transparency of the automation. Transparency refers to how well the automation communicates with the user, so that the user understands how the automation functions and whether or not it is behaving appropriately (Chen et al., 2014). This is directly related to the user interface, as increased transparency would likely take the form of more information about the system – whether this be an explanation of the system's actions, or likely future actions. Previous research has indicated that increased transparency improves usability and user performance (Mercado et al., 2016) as well as trust (Ososky, Sanders, Jentsch, Hancock, & Chen, 2014; Sanders, Wixon, Schafer, Chen, & Hancock, 2014). This may be able to guide design efforts and future applied research; preliminary research in an applied medical field (Bodenhagen, Fischer, & Weiglin, 2017) as well as aviation (Sadler et al., 2016) has seen positive results for automation systems transparency.

Although individual differences have been shown to influence the trust levels a user exhibits, there are few ways to account for this in practical real-world settings. In other words, it is unlikely that the U.S. Navy will screen for individual differences and determine who should and should not interact with automated agents based on their personality traits. For very specific roles that are highly reliant on human-machine teaming and trust, such as UAS operators, it is far more likely and encouraged. However, for interacting with automated agents on a training system, personnel selection for the role being trained for is most likely already set. With that said, practitioners are advised to be aware that individual differences can play a role in the trust and success of the automation, although beyond that awareness, they will have little recourse. Fortunately, prior to this point, and especially during prototyping and initial studies on trust in automation with specific systems, practitioners can collect individual differences data and control for it when doing analyses. This enables them to account for more variance, knowing that some is owed to individual differences. Using this knowledge in an experimental setting enables practitioners to see what other variables are increasing or decreasing a trainee's or instructor's, trust in automation.

As with all speech recognition and generation software, mistakes will occur with the CREATE system. Currently, speech recognition is not yet at the desired 90% or above accuracy rate in early prototyping, but it is consistently improving with more development. However, this means mistakes are inevitable. These automation failures will likely affect trust, and by extension, usage of the system. False alarms will present as "pushing" notifications to trainees which should not actually generate; misses will take the form of not providing an update to the trainee (or instructor) when an update should have been provided. Understandably, these automation failures will be a source of frustration for both trainee and instructor. However, mitigation through technological improvements as well as user interface displays can reduce frustration and improve understanding of the automation's status and functions. The limitation of speech generation technologies may create difficulty in differentiation between technological issues and trust issues – therefore the system limitation may drive usage and perceptions of CREATE at first. This creates issues not only in understanding trainee and instructor interaction with the system, but also performance measurement.

RECOMMENDATIONS AND CONCLUSIONS

After reviewing the trust in automation literature, and working through some of the research challenges themselves, there are recurring points of emphasis. Below are some recommendations which may be instrumental to performing future research efforts related to trust in automation.

- **Use an iterative design process, and make the human a key component**. When researching trust in automation, it is likely that the end goal is to improve the system. First and foremost, the way the human will interact with the system must be considered early on. Checking for trust in automation at the end of the design process is not useful in that there are likely fundamental changes which would need to be made in regards to how the system interacts with its users.

- **Consider the state of the automation being used**. If a lack of technological advancements inhibits the system from performing optimally, is it possible that users will become frustrated with the system because it does not perform the functions it should. This is a confound with trust, as the machine is not making "errors" per se, but the system is not necessarily at a high enough functioning level to adequately measure trust in automation.

- **Consider the goal of the research when deciding upon a measurement technique and methodology**. There are many ways to measure trust in automation, both behaviorally and subjectively. If the goal is to increase buy-in of a specific new system to users, it may be most pertinent to administer surveys and interviews to participants in order to capture their perceptions of the system and how they feel about interacting with it. If the goal of the research is to understand performance levels dependent on different automation types, and how failures may influence trust and performance, objective behavioral measures may be more appropriate.

- **Understand that automation is not always appropriate**. Automation, when riddled with error, can degrade performance below what it might be without automation. In this case, automation, which does not detect signals with a certain degree of accuracy may have a significant negative influence on performance. The addition of automation to systems should be implemented in such cases where it can alleviate the workload of an individual (e.g., the instructor in the case of CREATE); however, introducing automation for automation's sake is not necessary. Many non-automated systems (e.g., in training) produce good results and performance.

As with all research, there are limitations within the proposed applied studies. This is a very specific use case, and as such may not be directly applicable to all automated training. Along the same lines, there may be other key considerations when integrating automated systems into training that are not accounted for here – these likely differ based on specific use cases and technological capabilities. However, there is a need to study trust in automation, especially within the U. S. Navy as training systems become more advanced, and time, money, and personnel demands become higher. Human-machine teaming in the operational and training environments is on the rise, and as such, these environments must be understood in order to maintain Fleet readiness.

The current research attempts to alleviate some of these time, money, and personnel demands by understanding how and when automation is useful in training, and how the users (both trainees and instructors) will respond to the imperfect systems. Future research in this vein will include analyses of the CREATE system related to trust in automation, and how to increase trust in automation, as well as understanding how to better support trainees and instructors through the use of automation, when appropriate. By studying how best to design user interfaces and user interactions for trust in automation, the risks of system disuse and misuse can be mitigated. Because human-computer interaction significantly impacts user perceptions of technology, poor performance of speech tools often results in failed transitions and leads to lack of trust in systems. These systems require early and frequent testing in order to refine, and it is best to do so using the human as a key system component. This work is currently ongoing, and CREATE is a stepping stone use case involving trust in automation with both trainees and instructors.

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