Considerations for Adapting Training Technologies for Manned-Unmanned Teaming Operations

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ABSTRACT

The proliferation of automation within military contexts is a driving force in the effort to enhance and expand current manned-unmanned teaming (MUM-T) programs and policies. However, the shift from manned teaming to a collaboration between manned entities, unmanned entities, and automated and autonomous entities will also require a shift in the knowledge, skills, and attitudes (KSAs) trained for these teams. Not only will new KSAs be needed, but some currently trained KSAs will need to shift in function (e.g., communication will be different with autonomous team members than with human team members). This will effect training content as well as delivery potentially with new methods and technologies to support.

Overall, three broad constructs of concern for manned-unmanned teaming are: communication, trust, and workload balance between manned entities and their unmanned/autonomous counterparts. Communication will change vastly when operators are communicating with unmanned, and automated or autonomous entities. Appropriate calibration of trust is also a large barrier to seamless MUM-T coordination, given that new technologies (especially automation) often are either not trusted by operators, which directly affects their use (Dzindolet et al., 2003), or "over-trusted," resulting in automation-induced complacency (Parasuraman, Molloy, & Singh, 1993). In addition, the rapidly changing abilities of technologies, as well as the needs of the warfighter, will require that operators be able to manage their own workload, and take on or shed tasks when appropriate. From these three broad categories, several essential KSAs will emerge or fundamentally change from how they are currently defined.

It is also important to consider is the influence of these KSAs in defining the training technologies being utilized. It is likely that moving forward, the challenges presented by communication, trust, and workload balance can be partially mitigated through training technology solutions such as synthetic crewmembers, unmanned team members designed for appropriate trust calibration, and job aids for proper tasking allocation. The current paper will discuss these three broad constructs, the KSAs associated with each, and the prospect of currently developing technologies to support the training of these new and changing KSA needs. As a result, practitioners will be able to identify MUM-T training barriers within their own efforts, as well as successfully determine effective training solutions focused on those challenges.

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INTRODUCTION

Over the past decades, the Department of Defense (DoD) has focused significant resources toward the employment of unmanned aerial, ground, maritime, and space systems to support a vast array of missions. These unmanned systems are guided autonomously and/or by remote operation via ground or other manned assets. Many of the potential advantages of employing unmanned systems are clear. For example, unmanned systems have potential to provide better safety to our warfighters by expanding standoff capabilities from enemy forces and reducing exposure to life threatening tasks (e.g., improvised explosive device (IED) neutralization). Moreover, unmanned systems can support overcoming the limitations of human operators by potentially reducing workload, expanding continuity of operations, and augmenting situational awareness (DoD, 2010). Rogoway (2016) cites benefits of unmanned combat aircraft vehicles, such as lower cost, greater range, greater versatility, easier adaptation of hardware, and their inherent expendability/disposability. Unmanned vehicles do not require onboard pilots, and therefore pose fewer safety risks to the operators. Because of these many advantages, the fielding of unmanned systems to support tactical and operational objectives has expanded exponentially.

Unfortunately, as was noted by the Science Board (2012), unmanned systems are often developed before the concepts of operations (CONOPS) are fully understood and, therefore, these systems may not be used in actual operations as designers had intended. Rapid acquisition strategies for numerous unmanned systems have allowed them to bypass many of the burdensome constraints imposed by multiple stakeholders and bureaucracies. However, that has also meant that unmanned systems may not have been able to capitalize on the benefits of optimizing total (hardware/software/human) system performance resulting from a robust systems engineering and human systems integration approach to development. Of particular concern is the development of optimal human-autonomy interaction strategies. The potential pitfalls of applying automation without regard for its impact on human operators and on total system performance have been well-documented and a source of concern for decades. For example, Bainbridge (1983) warned that at times when automation fails or presents a significant anomaly, human operators are often called upon to use the very skills the automation had usurped to mitigate the malfunction or anomaly at the very time when issues are severe enough to exceed the capabilities of the automated system. Three and a half decades later, Strauch (2017) noted that the same issues forewarned by Bainbridge are every bit as relevant today, even as we have moved from the somewhat rigid, rule-based, automated systems of the past to the more independent and goal-oriented autonomous systems of today. Although now we may have a better understanding of the factors involved in effective human-autonomy teaming, there is still much to learn to optimize effectiveness via design and training.

Poor human-autonomy interaction continues to be cited as a causal factor in many of the most high-profile accidents of our times. Beyond the safety concerns of automation failures and the "surprises" that they engender, Parasuraman and Riley (1997) focused on the relationships between system reliability, mental workload, risk, trust, and how they impacted use of the automation, whether it be underutilizing (disuse), over-compliance (misuse), or optimal use. In sum, developers should be prudent in how they apply automation to tasks, and even more prudent in how autonomy is applied. Automated technologies in the DoD have historically ranged from simple threshold-based automatic systems onboard an aircraft (e.g., Stütz & Schulte, 2017) to fully autonomous vehicles (e.g., Downs et al., 2007). To clarify, while automated processes refer to a system based approach (e.g. software and/or hardware) to a manual and routine task by following a sequence of steps, autonomous systems seek to leverage advance techniques to replicate human processing (e.g., machine learning, artificial intelligence) increasing the decision-making capability of the system (Truszkowski, Hallock, Rouff, Karlin, Rash, Hinchey, & Sterritt, 2009). Because of the more independent nature of autonomous systems under development today, concerns about human-system interaction have transformed from manned supervisory control to concepts of manned-unmanned teaming (MUM-T). And, while there is indeed a large role for incorporating considerations regarding the human operator into system development, there are also challenges associated with how to prepare those operators to "team" with an autonomous unmanned system. For example, the Defense Science Board (2012) recommended the following operational courses of action as they relate to improved usage of autonomy:

- Include unmanned, autonomous system concepts (in all domains—air, ground, maritime and space) in war games and pre-deployment operational training.
- Ensure that lessons learned from using unmanned systems in the current conflict are broadly disseminated and are formally reviewed by the Military Services for training and operational improvements for current systems.
- Develop a unified (all Military Services and domains) feedback mechanism in which operators can input experiences and recommendations on autonomous system performance and behavior during both training and mission operations so that common experiences can influence autonomous system design and human-system collaboration.
- Develop operational training techniques that explicitly build trust in autonomous systems and validate projected manning efficiencies.
- Invest in modeling and simulation capabilities required to support early operation training to influence CONOPS development, mission planning, training, and logistics support.

Notably, each of the recommendations relies on training as a primary solution to the MUM-T challenges. Concurrent development of training systems allows for an early approach to understanding how best to train MUM-T processes. A review of current and historical performance issues can be used to derive knowledge, skills and attitudes (KSA) relevant for MUM-T. A few well-documented issues include: incomplete or inaccurate knowledge and mental models about the automated system's capabilities, and the inability to transfer what is learned in the classroom to performance in the aircraft (Sarter, Woods, & Billings, 1997); lack of operator confidence in being able to effectively use the automated systems and a mis-calibration of trust (Lee & See, 2004); and lack of situational awareness resulting from issues such as poor feedback, mode surprises, and undirected actions (Sarter et al., 1997). Operators will use autonomous systems in a way they perceive is familiar and trusted in interactions (De Keyser & Woods, 1990). This may limit or potentially hamper the human-autonomy teaming. For example, effective human teammates demonstrate backup behaviors where teammates know other team members' roles, responsibilities, and reliability (Salas, Sims, & Burke, 2005), and provide effective communication, such as feedback responses and good coordination where the right information is given to the appropriate teammate at the correct time (Cooke et al., 2013). Therefore, it is clear that moving from human-only teams to teams consisting of a mix of humans and autonomy will require the training of different KSAs. However, there is likely a benefit to performance, if the aforementioned teaming skills are used in the context of teaming with autonomous systems (Smith-Jentsch, Cannon-Bowers, Tannenbaum & Salas, 2008).

In anticipation of a heavy reliance on training to address challenges of MUM-T solutions as outlined by the Defense Science Board (2012), there is a need to continue improvements in training for manned platforms as well as an anticipated need for training technologies to account for unique aspects of MUM-T (e.g., communication, trust, workload). For example, leveraging unmanned and autonomous systems in war games and pre-deployment operational training has implications for the Live, Virtual, and Constructive (LVC) training environment. Involving platforms early in their development will increase safety risks and would therefore encourage integration via virtual and constructive assets potentially based on modeling and simulation (M&S) data constructed via early design and testing. This will allow researchers and developers to provide acquisition leadership with quantitative data to identify future challenges or adjustments to CONOPS, mission planning, and training pipelines. However, MUM-T also has known challenges for human operator training, including identification of strategies to maximize synthesis of data and employment of critical thinking skills to determine when and how to investigate automated decisions and recommendations.

Based on a review of relevant literature and historical references to human factors contributors to mishaps and safety issues, we have outlined three constructs for targeted focus in training solution design and development. Each of these broad constructs – communication, trust, and workload balancing – provides perspective into how to optimize the design of systems as well as associated learning objects that will inform training solutions, instructional strategies and methods, and training aids to support remediation or point of need training. The purpose of this paper is to provide insights into the efforts of researchers and instructional systems developers to better understand some of the KSAs required to operate and team with unmanned systems and to determine how training systems must evolve to address these shifting KSAs (see Table 1). In order to do so, this paper explores these three constructs to provide background, as well to suggest how KSAs will likely change with the increased focus on MUM-T. We present necessary or helpful changes in training technologies within these constructs to shed light on current changes being made in the training sphere and to highlight the shifts that must be made moving forward.

Table 1. KSA Taxonomy and Definitions

KSA Type	Relevant KSAs for Consideration	Construct(s)
Procedure Knowledge	Rule Application: The ability to use two or more facts to perform or carry out a known algorithm, procedure or set of steps including decision steps for a class of situations. The learner is able to respond to a particular class of stimulus situations with a specific class of performances.	Communication
Relational Knowledge	System Functionality: Functional and theoretical knowledge of the workings of an aircraft's internal systems and interactions.	Communication; Workload Balance
	Team Coordination: Mental model of organizational and team interaction constructs.	Communication; Workload Balance
	Situation Assessment: Awareness of surroundings.	Workload Balance
Situated Problem Solving	Deliberate Decision Making: Well thought out decisions made prior when needed for effective action.	Communication; Trust
	Troubleshooting: The ability to systematically and/or analytically evaluate causes for malfunctions/faults in an aircraft.	Communication
Perceptual Skills	Cue Pattern Recognition: Identification/discrimination categorization that is outside of normal and safe parameters	Workload Balance
Attitudes	Trust in Automation: Calibration of trust in autonomous diagnostic software.	Trust
	Team Concept: Willingness to work as a team, get a second option, or share knowledge.	Trust

COMMUNICATION

Changing KSAs

Human-only teams develop a shared mental model of the performance environment, the equipment required, and the expected interactions with teammates (DeChurch and Mesmer-Magnus, 2010). Having shared knowledge structures and mental models of roles, responsibilities, and interaction patterns allow improved teaming performance, in which each teammate aligns their behaviors to develop expectations and make predictions of others' actions to effectively communicate and coordinate tasks (Van den Bossche, Gijselaers, Segers, Woltjer & Kirschner, 2011). In human-autonomy teaming, shared mental models and communications modes may not be possible with the current technology. As part of this, addressing relational knowledge KSAs such as system functionality and team coordination will be essential. Further, given that communication is identified as a critical component for effective teaming for human-only teams (DeChurch & Mesmer-Magnus, 2010) and MUM-T (Sticha, Conzelman and Thibodeaux, 2012), the human will have to learn how to communicate differently with their machine counterparts.

Communication is a transfer of information between two entities and is complex in nature as information can be conveyed and interpreted in many ways. Human-human communication is conducted using a variety of methods, such as spoken words, inflection (pitch and tone), nonverbal body language, written text and visualization, such as symbols, maps and logos, in both formal and informal forms. In human-autonomous communication, the machine must present information that the human can understand. The communication of information affects situated problem solving KSAs such as deliberate decision making and troubleshooting. Automation transparency is a form of communication to provide the human insight into the system's behavior, intentions, and goals (Panganiban et al., 2020). The human must learn knowledge (e.g., system functionality, team coordination models) relating to communicating with autonomous systems effectively, such as data location, communication modes, rule applications, system functionality, and team coordination dynamics, while maintaining situational awareness of the current and expected modes to gain the information. This information will influence strategic and dynamic decision-making skills (e.g., deliberate decision making, troubleshooting) for evaluating the autonomous system's performance. Effective communication and system transparency can support the attitudinal components such as the calibration of trust (Endsley, 2017) and increase confidence in the human-autonomy teaming concept. Dzindolet et al. (2003) also noted that training operators to appropriately use and trust these systems should include instruction on how the system works in addition to providing opportunities to use the system. Continuing training may be needed as automated capabilities increase for more human-out-of-the-loop tasking; this continual capability evolution reinforces the importance of effective communication (Chen, Lakhmani, Stowers, Selkowitz, Wright, & Barnes, 2018).

Effects on Training Technologies

The nature of communication will change as we shift from human-only teams to MUM-T supported by technology and automated components. The most effective MUM-T strategies and, therefore, the training of those strategies is heavily dependent on system design decisions related to the level(s) of system autonomy (e.g., manned systems, remotely piloted aircraft, semi-automated components, and totally autonomous systems and aircraft). How to best facilitate understanding and cooperation required between operators and the technology is a key question when considering MUM-T communications training. This is addressed in part by current research regarding the benefits of synthetic agents as teammates (e.g., Demir & Cooke, 2014). However, though synthetic teammates can perform many of the necessary tasks in a team, team dynamics between humans and their synthetic teammates still need to be improved (Demir et al., 2016; McNeese et al., 2018).

In addition, speech-based interfaces may provide a more intuitive communication method with systems. That is while systems traditionally interact via visual or auditory alerts, speech-based interaction provides a more familiar way of interaction with technology. However, speech technologies currently lack accuracy, and techniques and performance vary greatly, depending on the sophistication of the speech capabilities. Automatic Speech Recognition (ASR) capabilities are promising, although have not yet become a widespread feature in many training systems. This is likely due to the inherent complexity of modern ASR systems. For example, the system must first be able to generate an accurate text representation of the user's speech. , Form an understanding of what that text means the system must generate an accurate acknowledgement of the request. Finally, the system must perform the appropriate behavior required of the request, while simultaneously tracking the previous and anticipated dialog of the conversation (Stensrud et al., 2015).

A possible mitigation to this complex process is to provide training systems with a custom grammar and vocabulary focusing solely on the doctrinal words and phrases used during training and operations. While this will hypothetically increase recognition and accuracy, the ASR may not be as robust as more "generalist" ASR systems and will likely suffer failures when words are spoken outside the custom grammar or vocabulary. Although custom grammars are expensive to develop, there are strides being made to decrease the time and resources required to generate them, as well as to enable users to modify their own grammars, without the need of speech engineers (Atkinson et al., 2017). Additional research questions remain, such as whether the way users of MUM-T systems communicate with their teammate should be standardized for all users, or whether communication flow is smoother if users are able to customize their speech interaction with it. In theory, custom phrasing per user could increase the recognition success rate, leading to a user perception of more reliability, leading to more trust within the manned-unmanned team. However, implementation standards should be carefully evaluated to ensure that customization does not introduce increased ambiguity and misinterpretation of human speech resulting in increased response errors.

TRUST

Changing KSAs

Trust is a complex construct, tied to many different KSAs, including knowledge about the other entity being trusted, skills related to interacting with that entity, and attitudes held that affect that trusting relationship. However, understanding impacts of KSAs such as trust in automation and team concepts, as well as deliberate decision-making regarding trust will be most critical. As MUM-T shifts toward more automated components, including autonomous vehicles, the KSAs trained will need to reflect the shift to higher degrees of automation to include conditions in which automation is even considered a team member. Previous research has indicated that human-automation trust (HAT) has both significant similarities and differences to human-human trust (Jian, Bisantz, & Drury, 2000; Madhavan & Wiegmann, 2007). Automation offers information differently than humans do – in terms of appearance, interaction, capabilities, and familiarity. One of the largest influences on trust in automation is the automation's reliability (Hancock et al., 2011). If automation is unreliable below a certain threshold (approximately 70%), it can degrade human operator performance rather than augment it (Wickens & Dixon, 2007). Therefore, it is important for operators to appropriately calibrate their trust for the automation in question, which will support proper use of the system. Failure to calibrate appropriately will result in not trusting or over-trusting the system, which may cause disuse or misuse, respectively (Parasuraman & Riley, 1997). As a result, operators must be able to properly monitor and assess the system's responses in order to calibrate (and recalibrate) trust effectively.

The proper calibration of trust requires taking in the information in a rational, problem-solving way and having the appropriate attitude of a propensity to trust the automation. Some research has found that implicit attitudes toward automation have an effect on trust in that automation (Merritt, Heimbaugh, LaChapell, & Lee, 2013). When shifting to teams that more heavily feature automation, these implicit attitudes will need to foster positive collaboration within teams. Though difficult to train an attitude, propensity to trust can be measured through self-report means (Jessup, Schneider, Alarcon, Ryan, & Capiola, 2019). Though operators continually work with technology, automation is changing the tasks operators execute and the way those tasks are completed. Operators must have a propensity to trust automation to take on these previously human-completed tasks. This is a significant part of individual adoption of new technologies, which can drive organization-related automation policies.

Effects on Training Technologies

Training technologies must serve two important functions to train trust-related KSAs: train operators to calibrate trust effectively and maintain a high enough fidelity within training simulations to the actual system. In order to mitigate some trust calibration concerns, research has investigated ways that design of systems and interactions can contribute to appropriate trust calibration. One of these ways includes automation transparency – the degree to which the automation communicates its goals, actions, and reasoning (Chen et al., 2014). A substantial amount of research has indicated that a higher level of automation transparency can benefit human-machine performance, support proper trust calibration, and increase operator trust (Wortham & Theodorou, 2017; Yang, Unhelkar, & Shah, 2017; Matthews, Lin, Panganiban, & Long, 2019). Depending on the complexity of the automated training system, or automation modeled in a training system, it may be appropriate for the system to communicate varying amounts of different types of information (e.g., goal, reasoning for actions, actions). While this continuum can range from "black box" automation, where the operator has no awareness of the system's actions and reasoning behind those actions, to a maximum state of information communication such as code visibility, designers must carefully consider the appropriate level of transparency for the specific use case or environment. Other design measures can be taken to foster proper trusting of these systems, including the use of clear, consistent, concrete details (Lee & See, 2004).

As previously recognized, trust in automation will influence the performance not only of students, but also of instructors (Anania, Killilea, & Atkinson, 2018). Automation's integration in training systems (for MUM-T and beyond) can re-allocate tasks that instructors previously executed (e.g., roleplaying other entities in a task that would normally require additional human participants). This leads to a reduction in necessary manpower, time, and ultimately cost. When designing automated training systems, instructor interfaces can benefit from following some of the same guidelines to foster appropriate training calibration. It is important that operators be able to trust the technologies they interact with (when appropriate), as distrusting automation, especially when distrust is unfounded, can significantly increase operator workload, and overburden human members of the team. This is true for both instructors and students in the training domain, as well as anyone in the operational domain. Given the tight connection of trust to usage of the system, these constructs are inherently tied to workload-based KSAs and system design.

WORKLOAD BALANCE

Changing KSAs

Before the technological advancements of more autonomous systems, automated systems utilized less complex data sources, simple compartmentalized input-output algorithms with often predefined, rigid outputs. Identified human performance issues were limited to "errors in interpretation of the data, maintaining situation awareness (SA) or permitting flawed outputs" (Panganiban, Matthews & Long, 2020, p. 174). As the systems became more autonomous, their capability to interpret the environment and develop courses of action allowed a shift of specific task loading away from the operator. This leads to the system functioning more like a collaborative teammate than a tool. However, with increased complexity, the human has less direct insight into the system's processes and control of its actions (Panganiban et al., 2020). In essence, the autonomy is a "black box." This variation in task coordination and collaboration teaming interactions with the evolving autonomous system leads to additional performance issues and increases the difficulty to learn (French, Duenser, & Heathcote, 2018). This situation influences KSAs related to relational knowledge (e.g., system functionality, team coordination, situation assessment) and perceptual skills (e.g., cue pattern recognition).

Human performance is highly dependent on workload,cognitive or otherwise (Parasuraman, Sheridan, & Wickens, 2008). A workload that is too heavy or too light can degrade performance and contribute to a loss of situational awareness (Proctor and Zandt, 2008; Tsang & Vidulich, 2006). It has been demonstrated that automation and autonomous systems can be utilized with the goal to reduce human workload, increase situational awareness, and improve system performance. However, the human teammate gains an additional supervisory role for directing, overseeing performance, and taking over tasking when necessary as well as becoming a collaborative partner (Endsley, 2017). Performance issues arise when the human lacks the skills or is too task-saturated to identify autonomy errors by monitoring the system and performing corrective actions when an unexpected or incorrect action is performed (Kaber & Endsley, 2004). Another performance issue arises when the human becomes complacent and over-reliant on the system to perform tasks and fails to correctly monitor the actions for errors (e.g., Bailey & Scerbo, 2007).

Effects on Training Technologies

The proliferation of autonomous systems presents new tasks, KSAs, and MUM-T roles for operators that will affect workload and necessitate the development of new training systems. However, on a more general level, training systems must teach operators how to deal with shifting workload demands such as by task shedding and gaining whenever possible to maximize tactical decision-making. In operational systems, this is largely supported by the concept of adaptive automation, which allows both the user and the system to allocate functions of a task to either the human or the automation (Inagaki, 2003). When developed prudently, adaptive automation has been shown to improve situational awareness, benefit operators during high workload times, and ultimately enhance performance (Kaber & Riley, 1999; Parasuraman, Cosenzo, & De Visser, 2009; de Visser & Parasuraman, 2011). However, there have been even more examples of poorly designed adaptive automation applications that have produced the opposite effects often at times when operator task load is at its highest (Weiner, 1989: Billings and Woods, 1994). Operational systems that currently use adaptive automation can, in part, help with the requisite task shedding and gaining. The training systems involved for these operational processes should mimic the functions of real-world adaptive automation applications, potentially through embedded training that is part of the tactical system capabilities. In addition, training system designers need to ensure they provide training on the KSAs needed for specific operator tasking. For example, training systems may require the capability to adjust function allocation in order to train students to perform under different constraints in a flexible way (such as may be experienced with optimal/optional crewing situations).

Opportunities may also arise to train in variable workload systems, such as optionally piloted vehicles in which the pilot in the vehicle is able to choose when and how they interact with different systems (Miller, Goldman & Musliner, 2002). This would mitigate the possibility of work overload and allows the pilot to focus on other tasks. As roles and responsibilities shift, the human must have the correct mental models and team coordination knowledge to be able to identify changes in their workload leading into, during, and after utilization of each mode configuration and maintain flight skills in order to transfer or take back control of selected tasks. This could mean that the pilot would operate the aircraft in full manual mode to a fully automated controlled mode depending on what he or she felt was appropriate (Miller, Goldman & Musliner, 2002). Training in systems that allow for crewing changes could be instrumental in providing opportunities to practice identifying and constructively managing workload.

CONCLUSIONS

Previous research into automated and autonomous systems has yielded a wealth of lessons learned that can be expanded to the emerging needs of MUM-T operations, where operators are teaming with technology more than simply providing supervisory control. In anticipation of training being the opportunity to correct for any limitations in design or mismatches between expected and operational uses for automated and autonomous technologies, considering current best practices that can be scalable and flexible to emerging needs will be critical to MUM-T operational success. Three key broad constructs were discussed: communication, trust, and workload balance. Shifting KSAs and the resulting necessary changes in training systems are necessary to investigate early on in the process, to maintain optimal training and operational readiness.

For communication, aspects of crew resource management (CRM) are likely to transfer to MUM-T training. However, expanding traditional CRM to investigate tools necessary to aid in building shared knowledge models such as automation transparency will be an important factor in ensuring effective communication among human and non-human teammates. Tactical design decisions on how humans interact with various automated or autonomous systems will ultimately impact the training needs. While research in the last decade on use of synthetic teammates and speech systems shows promise for communication and coordination, research to evaluate multi-modal interfaces to avoid impacts to workload simply by adopting a standard human-to-human interaction method may be beneficial in addition to continuing to advance these agent- and speech-based systems.

Research regarding trust and trust calibration provides insights into considerations for selection, interface design, and training. While some individuals may be better suited due to attitudes and previous experiences to more readily self-calibrate trust with automation, there will be opportunities to increase trust and support trust calibration within operational systems and training. One important shift in system knowledge training may be to ensure that there are targeted modules and refresher training that provide operators information on the system reliability and limitations. Additionally, expanding on automation transparency research will be a critical component of the human-machine interface design for operational systems as well as training systems development. First, investigating implications of automation transparency levels on operator performance, situational awareness, and workload in specific use cases will inform user interface design. However, although there may be an optimal solution for expert users in an operational setting, a technology scaffolding approach (i.e., adjusting the transparency up or down based on trainee skill level) may afford students with opportunities to calibrate trust and identify specific strategies for technology implementation. Further, a lack of transparency on an instructor's system not only influences their adoption of technology and workload, but it also affects their ability to debrief trainees effectively. If an instructor does not understand the actions taken by the automated or autonomous systems, it becomes impossible to provide diagnostic feedback that is critical to increasing learning and performance.

The final construct of interest is workload balance. Automated and autonomous systems may enable workload reductions due to offloading previously manual tasks such as synthesizing multiple system inputs, or they may increase workload if operators must conduct significant monitoring to ensure accuracy or avoid losing (or having to regain) situational awareness. Continuing to explore the operational and training impacts of technologies such as adaptive automation to afford operators with opportunities to adjust based on operational tempo and competing priorities shows promise. Additionally, increasing focused training on optimizing such systems based on missions, tasks, or individual differences, as well as providing vigilance training to ensure operator awareness of the dynamic nature of operational missions, will likely be necessary focus areas.

As technology rapidly advances and the doctrine for MUM-T evolves (Stitcha et al., 2012; p. 20), there remain opportunities to increase our understanding of environment specific constructs to address the challenges that exist for ensuring effective and efficient MUM-T operations. To ensure that operators are provided training tailored to the KSAs required for MUM-T operations and environments, there is a need to revisit both training needs and technologies. Continuing a close relationship between system designs and training considerations during the development of autonomous technologies will be critical to providing effective rapid responses to future needs, with focus on at least three critical constructs.

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