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ASSURE

Alliance for System Safety of UAS through Research Excellence

Drexel University

Oregon State University

Kansas State Polytechnic

A26: Establish Pilot Proficiency Requirements Multi-UAS Components

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Table of Acronyms

Acronym	**Meaning**
3D	Three dimensional
ATR	Automatic target recognition
CFR	Code of Federal Regulations
DAA	Detect and avoid
FAA	Federal Aviation Administration
HITL	Human in the loop
ISR	Intelligence surveillance reconnaissance
LOA	Level of autonomy
NAS	National Airspace System
OSPAN	Operation Span
PAC	Perceived attentional control
SA	Situation awareness
SAGAT	SA Global Assessment Technique
SART	SA Rating Technique
sUAS	Small UAS
UAS	Unmanned aircraft system
UAV	Unmanned aerial vehicle
WMC	Working memory capacity

Executive Summary

Commercial and public safety Unmanned Aircraft Systems (UASs) are currently limited by the 14 Code of Federal Regulations (CFR) Part 107.205 prohibition on operating multiple aircraft by one person. The public as well as UAS commercial operations in applications, such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, and infrastructure inspections will benefit from modification to this prohibition. The FAA-ASSURE study that this literature review supports will help to inform FAA regulations and industry standards addressing single pilot and multi-UAS operations. This literature review is designed to inform ASSURE researchers and FAA sponsors of the findings from published studies and to identify research gaps.

The research team reviewed approximately 100 manuscripts. Previous works mostly focused on Human-in-the-loop (HITL) studies, with an emphasis on human factors limitations for operating and monitoring multiple sUAS conducting surveillance, reconnaissance, target detection/classification, and/or search missions. To evaluate the effect on the operator, these studies used performance measures, including target detection rate and response times as well as subjective measures including perceived workload, trust in autonomy, and situation awareness. Some of the studies evaluated levels of autonomy needed for different tasks and others explored the effects of static (remain at the same level) or adjustable autonomy based on operator workload or performance.

Perhaps one of the biggest findings is how little research is available on the factors, effects, and their interactions regarding the control of multiple UAS across different phases of flight (takeoff, departure, enroute, mission, arrival, landing and ground operations). Some other research gaps include the effects of different levels of education and training of crew roles (including the operator in command); the minimum crew roles necessary for different types of operations, and the implications of system autonomy; climate; airspace; type of aircraft (fixed-wing, rotorcraft, hybrid); communication reliability; task/mission composition; the physical multiple UAS system composition; and more.

The ASSURE research team will begin to improve understanding of these factors by modeling loosely coupled tasks where multiple vehicles conduct independent tasks (e.g., drone package delivery). This effort will demonstrate and provide a better understanding of the factors affecting a single operator's safe control of multiple UAS as well as the interactions and relationships between the key components. Additionally, researchers plan to conduct a small HITL study (on-campus UAS delivery) to demonstrate, further understand, and/or validate some of the modeling findings.

It is expected that this project will generate even more questions that will need to be resolved before the FAA is able to institute substantial regulations and guidelines. However, by the end of this project researchers and the FAA will have a much clearer understanding of what further insight is needed to safely allow multiple UAS operations in the nation's airspace.

1 Introduction

Commercial and public safety UAS are currently limited by the Part 107.205, which prohibits operating multiple aircraft by one person. A modification to Part 107.205 will benefit the public as well as UAS commercial operations in applications such as package delivery, precision agriculture, crop and wildlife monitoring, emergency management, and infrastructure inspections. The study that this literature review supports will help to inform FAA regulations and industry standards addressing single pilot and multi-UAS operations. This literature review is designed to (1) inform ASSURE researchers and FAA sponsors on findings from published studies and (2) identify research gaps that are outside the scope of this project but need further study in order to safely integrate multiple UAS operations into the National Airspace System (NAS).

2 Literature Identification

The identification of the relevant literature related to the pilot proficiency requirements for a single pilot conducting multiple unmanned aircraft systems (multi-UAS) operations required identifying appropriate search terminology, as shown in Table 1. The search terms focused on the type of vehicle (the *UAS* terms), on multiple vehicles (the *group* terms), and on the human operator serving as the supervisor (the *interaction* terms).

Table 1: Literature review search terms by category.

UAS	**Group**	**Interaction**
Autonomous micro air vehicle	Cooperative	Human-autonomy teaming
Remotely piloted aircraft	Coordinating	Human-robot teaming
Remotely piloted vehicle	Distributed	Human-swarm interaction
Uninhabited air vehicle	Multi	Multiple robot control
Unmanned aerial system	Multiple	Multiple robot control
Unmanned aerial vehicle	Swarm	Multi-robot coalition
Unmanned aircraft		Multi-robot teams

The manuscripts were required to meet explicit review criteria. The basic criteria required manuscripts written in English that appeared in peer reviewed or high quality sources between 2010 and 2020. Manuscripts were excluded if they did not provide sufficient detail (e.g., lacked a detailed experimental methodology) or contained errors (e.g., inconsistent results). The manuscript evaluations were required to focus on operator performance; thus, those the failed to do so for any reason, including not reporting experimental results related to operator performance, were excluded. Manuscripts were also excluded if the mission or task focus was not relevant, such as the operator not directly controlling or supervising UAS.

The most relevant literature sources focus on human factors and robotics sources. A summary of the publication sources for the included manuscripts is provided in Table 2.

Table 2: Manuscript sources

Publication	Count
Cyber-Physical Systems	1
Ergonomics	2
Frontiers in Psychology	1
Human Factors	8
IEEE Transactions on Human-Machine Systems	1
IEEE/RSJ International Conference on Intelligent Robots and Systems	1
International Journal of Human-Computer Interaction	1
International Journal of Human-Computer Studies	1
Journal of Cognitive Engineering and Decision Making	6
Journal of Experimental Psychology, Applied	1
Proceedings of the Human Factors and Ergonomics Society Annual Meeting	30
Theoretical Issues in Ergonomics Science	2

3 Review Results

This section highlights the findings of the reviewed manuscripts. The findings are organized to help inform regulations and research gaps for multi-UAS control. The first subsection addresses the methodological approaches employed in the studies to help to identify the fidelity of the work. The second subsection highlights the types of evaluation measures utilized in the reviewed literature, including characterizing them as objective or subjective and whether they can help to measure aviation safety, pilot capability, efficiency, and productivity. The third subsection addresses a set of results related to operator characteristics that can help to define requirements for training and pilot certification, followed by a subsection specifically focusing on training interventions for multi-UAS control. The fifth subsection addresses missions and associated task characteristics that can inform research related procedures as well as scenario definition. The system and aircraft characteristics that can help to characterize the generalizability of the work with respect to architecture and sUAS heterogeneity is reviewed. The term “multi” can range from two to many; thus, the seventh subsection addresses aircraft group characteristics. As multi-UAS control may employ high levels of autonomy on the aircraft as well as within the control station, the eighth subsection focuses on autonomy and human-autonomy teaming, while the final subsection addresses control station characteristics.

3.1 Methodological approaches

Considering different methodological approaches provides higher quality information and yields results that are more generalizable to the project’s goals. For example, field tests in mission relevant contexts provide more directly applicable results than experiments in which the UAS’ behaviors are emulated, called Wizard of Oz experiments. The vast majority of the included manuscripts were human-in-the-loop studies conducted using simulations that incorporate partial sets of operator required tasks, as shown in Table 3.

Table 3: Methodological approaches.

Type	Count
HITL	50
Computational Model	2
Design	1
Interview	1
Operational concept document	1

3.2 Evaluation measures

Gathering information that can inform regulations with respect to the pilot proficiency and training requirements, procedures, and control station requirements and guidelines for multi-UAS control requires understanding relevant evaluation measures, also called dependent measures. Such measures need to support the assessment of aviation safety, pilot capability, efficiency, and productivity [1]. The reviewed evaluations encompass a range of dependent measures related to human performance, where some were mission specific.

Many of the evaluations addressed accuracy [2–26] and related signal detection measures, including detection or hit rate, correct rejection rate, false alarms, sensitivity, and response bias [21, 26, 27]. Only three evaluations addressed safety: vehicle to vehicle damage and vehicle to hazard damage [28], UAS loss [20], and time of safety violation condition [10]. As operators may employ a speed-accuracy tradeoff, several evaluations considered efficiency measures including response or task completion time [3–7, 10–12, 17–20, 29–36].

The evaluations predominately incorporated subjective performance and usability measures. The most frequent measure was perceived workload measured via NASA-TLX [37] (i.e., [2, 7, 8, 11, 13–16, 23, 25, 26, 28, 30, 32–36, 38–43]) and other common measurements [4–6, 9, 29, 44, 45]. A few evaluations employed related workload measures, such as perceived task difficulty [3, 4, 6, 17, 29, 39] and level of busyness [9, 44, 46].

A set of measures related to trust in, and usage of the autonomy were used. Trust in autonomy was measured in some studies [5, 6, 9, 12, 29, 33] using variants of Jian, Bisantz, Drury's [47] trust scale, while other studies [7, 11, 28, 30, 42] used other instruments. Additional, subjective trust measures assessed compliance with the autonomy [24, 25, 28, 48], reliance on the automation [12, 14, 15, 24, 48], competence, faith in the system and perceived reliability [24, 30], among others.

Situation awareness was the third most common measure, where common subjective tools were used. The different situation awareness methods included SA Global Assessment Technique (SAGAT) [49] (e.g., [30]), SA Rating Technique (SART) [50] (e.g., [11, 42, 45]) and other types of queries (e.g., [2, 7, 26, 43]). Some evaluations did not specify the exact situation awareness assessment method (e.g., [4–6, 29, 44]).

Design and usability measures were employed to address algorithm parameters and display design. Calhoun and colleagues used adequacy of autonomy feedback [6, 29, 44] and impact of autonomy on performance [5, 6, 29, 44]. Specific usability measures included perceived overall usability [33, 36, 40, 51], ease of use [7, 23, 52], preference [17, 22, 27, 36], interaction modality [8] and comfort [52]. Different types of self assessment measures were considered, including perceived task performance/accuracy [3, 5, 6, 9, 17, 22, 29, 44, 46], subjective task certainty [22], perceived speed [17], self-confidence [9, 11, 22, 23, 46], perceived understanding [22], and perceived responsibility for accurate performance [23].

While subjective measurement of relevant human factors issues can provide useful insight into general task perceptions, the over-reliance on subjective assessments of human factors poses a pressing challenge to effective evaluation of pilot needs in multi-UAS control. For example, while subjective workload measures like the NASA-TLX often correlate with overall perceptions of a task, the fact that such assessment takes place post-hoc (i.e., after task completion) and is temporally decoupled from explicit task components, makes it especially difficult to appreciate with any confidence what task components specifically drive any changes in such measures. In other words, while it is possible to detect higher degrees of workload, it is often very difficult to determine exactly what specific aspect of the task or environment may be driving the increases, which is naturally important for workflow optimization. This is perhaps endemic of a common disconnect observed in the literature; studies often fail to simultaneously measure objective task performance (i.e., mission time, errors) measures concurrently with subjective measurements, like trust in autonomy, situational awareness or even perceived competency/efficacy. The omission of more objective performance criteria makes it difficult to appreciate how subjective perceptions conceptually link to, and inform, actual task completion, which becomes especially problematic when considering normal individual differences in operator performance. Without the ability to anchor subjective assessments to objective differences in performance, it becomes nearly impossible to determine whether any differences in these subjective estimates are (1) a function of user competency, or (2) driven by other more broad reactions to the task environment. Further, given the very performance driven nature of multi-UAS domains (e.g., package delivery), it seems necessary to capture objective aspects of task performance so that implementation of regulatory guidance can be validated more consistently.

3.3 Operator characteristics

The requirements for training and pilot certification for multi-UAS operation are understudied. The types of individuals who will be ideal for multi-UAS operations in domains, such as package delivery, may differ significantly from current UAS operators engaged in domains, such as homeland security. Thus, developing multi-UAS systems' regulations for pilot proficiency and training requires considering a range of operator characteristics and associated measures. This section's findings are related to these characteristics, where performance may be enhanced or diminished due to individual differences.

3.3.1 Pilot experience demographics

Obtaining a remote pilot certification for a single UAS requires knowledge evaluated per the requirements in 14 CFR Part 107.73 [53]. An open research question is whether remote pilots of multi-UAS require the same level of piloting knowledge, less knowledge, or a different set of knowledge. Two evaluations mentioned unmanned vehicle experience: one reported participants with UAS experience [10]; another reported some robotics experience [22].

Generally, the multi-UAS HITLs particpants did not have 14 CFR Part 107.73 certification, nor any piloting or other related aviation experience. Participants were frequently students [2,8,11,14–16,18–21,24,25,27,31,33–35,38,41,46,54–56], or were reported as either having no pilot experience [44] or their experience was unspecified [7,9,12,36,48]. Additional manuscripts reported participants with no robot control experience [13,26,32,43], computer users [28], or having various backgrounds with no unmanned aircraft experience [30]. Even when the participant pools were composed of military affiliated personnel, they reported no piloting experience [5,6,17,23,45], with the exception of [3].

As the minimum automation requirement for the vehicles as well as the operator control station are undefined, it continues to be unclear what piloting experience multi-UAS operators require. The proficiency requirements may be related to a large number of factors, thus, it will be important to determine whether the current literature findings with the current set of participants are relevant.

3.3.2 Gender differences

The FAA predicts that the growth in the commercial UAS sector will continue [57]. Females held only 6.8% (10,818) of the 160,302 remote pilot certificates in 2019, [58]. It is unclear whether this trend will continue and whether any potential changes in gender demographics will impact the sector.

Each study tends to include more male participants. Only 43 studies reported participants' gender, of which only 2 were gender balanced and 28 included more male than female participants. Relatively few studies analyzed the influence of gender with respect to multi-UAS control. Video game experience and gender were investigated as predictors of stress and performance [14] in an evaluation that explored the effect of workload and Level of Autonomy (LOA) on participants' performance using a simulated multi-UAS supervisory control station. Gender differences were not evident when the analysis was controlled for gaming experience.

An important consideration is whether the FAA and industry need to be actively working to increase the number of females seeking remote pilot certificates. Further, analysis of such systems by the research community to ensure more balanced participant pools that will accurately reflect the anticipated workforce pools.

3.3.3 Video game experience

Video game experience is often presumed to positively influence the ability to successfully complete tasks for multi-UAS and/or multi-vehicle control. Experienced gamers have been found to have better visuospatial attention skills than pilots, but have similar aircraft control skills [59]. Additional results, by Spence and Feng's [60], indicate that playing action games can impact sensory, perceptual, and attentional abilities, which are important for many spatial cognition tasks and likely multi-UAS control as well.

Generally, individuals with video game experience exhibit better performance and situation awareness (SA) in multi-vehicle control experiments. The participants tend to provide better subjective measures, such as perceiving lower workload and trusting the autonomy more, particularly in higher taskload environments. For example, Chen and Barnes [7] investigated participants supervising a team of ground robots with autonomy of varying reliability levels. Video gaming experience was associated with overall multitasking performance.

When supported by an autonomous system, frequent video game players had significantly better perceived SA than infrequent gamers. Also frequent video gamers' subjective workload assessments were significantly lower than those of infrequent gamers.

Performance benefits were identified based on video game experience for a three vehicle convoy mission [26], where gamers had higher SA scores than non-gamers. Additionally, non-gamers had a liberal response bias (i.e., more likely to respond that there was a target during a target detection task). This difference in decision strategy, as a function of video game experience warrants further investigation as non-gamers may be compensating for their lack of spatial awareness or experience.

Surveillance will be a common multi-UAS task. Video gaming expertise was correlated with performance for a surveillance task (weapon release) [14]. First-person shooter game experience predicted post-task engagement. Participants with more action game and first-person shooter game experience were more accurate, relied more on the autonomy, and exhibited less task neglect. Those participants with video game experience also trusted the autonomy more during higher task load conditions, and experienced lower stress and worry.

A multi-unmanned experimental vehicle planning task was used to examine the level of information necessary to create an effective and transparent interface that supports human-agent teaming [33]. The results showed that gamers did have faster response times, but this was confounded with other demographics.

Video game experience appears to play an important role in operator performance and while this is an important finding, a gap is identifying the unique aspects of gaming experience that may benefit future multi-UAS operators. Open questions include: do gamers possess unique individual differences and what can future operators learn via training that permits them to be as proficient as gamers?

3.3.4 Spatial ability

In aviation, spatial awareness impacts safety as human operators need to consider the relative locations of objects in the environment [61]. Thus, high spatial awareness may be a critical differentiator for the selection of multi-UAS system pilots.

Multi-vehicle control researchers found benefits for individuals with better spatial ability scores as measured using tests, such as the Cube Comparison Test [62] and the Spatial Orientation Test [63]. Participants with higher spatial ability detected more targets when using robots with varying autonomous navigation reliability levels. Participants with better spatial ability also interacted more with the video feed interface than participants with lower spatial ability [7], which may indicate more effective scanning performance or capacity to consider additional visual information. While supervising a three-vehicle convoy, where autonomy fully supported the vehicle spacing task and partially supported route planning, participants with higher spatial ability maintained higher SA than those with low spatial ability [26]. Autonomy was able to raise the performance of participants with lower spatial ability. The autonomy assistance helped participants with low spatial ability improve their SA. The lower spatial ability participants also increased their sensitivity in the target detection task with the additional autonomous support.

Spatial ability is tied to better performance for tasks relevant to multi-UAS operations; however, autonomous capabilities will raise the performance floor for those with lower spatial ability. Thus, two considerations are warranted: 1) selection of personnel based on spatial ability and 2) the autonomy requirements necessary to support personnel with lower spatial ability.

3.3.5 Working memory

Working memory capacity can predict performance in many complex tasks, which may provide guidance when selecting operators for multi-UAS systems. It is well established across domains that working memory capacity (WMC) reflects differences in the capacity to control attention with both automatic and controlled processes [64]. The reviewed literature indicates benefits of higher WMC for multi-vehicle control. de Visser, Shaw, Mohamed-Ameen, and Parasuraman [31] studied working memory differences as impacted by the effects of taskload and relevant message traffic for single-human/multi-UAS system performance. WMC was measured using Operation Span (OSPAN) [65], which showed that eight vehicles can be monitored relatively successfully, albeit less so in higher taskload conditions.

An investigation of participants engaged in a multi-unmanned experimental vehicle planning task examined the level of information necessary to create an effective and transparent interface to support human-agent teaming [33]. Participants completed the OSPAN task [66] to measure WMC, and those with higher WMC had the best performance with respect to autonomy usage with the low transparency interface.

Panganiban and Matthews [41] conducted a study where the goal was to supervise three or six UAss to search for as many targets as possible while avoiding hazardous regions. The participants also updated a set of information held in working memory, such as a letter (Letter Memory task) or a word (Keep Track task). Participants received neutral or negative feedback regarding their performance. The ability for executive functioning, which is a critical component of WMC, was measured using inhibition, switching, and updating to predict UAS operator performance and subjective state under stress [41]. High letter memory was associated with better performance as measured by the command ratio (total number of target engagements divided by the number of target assignments) regardless of taskload.

Better team working memory scores were associated with superior team performance when taskload and the reliability of an autonomous decision aid's message traffic was manipulated using a multi-UAS simulation for an air defense task [54]. Thus, a participant's working memory, even when considered in combination with another team member, can enhance overall human-system performance for a supervisory control task.

Given the multi-tasking nature of multi-UAS control, further investigation is required regarding the impact of working memory capacity on operator selection criteria for multi-UAS systems. Control station information requirements and display design recommendations need to consider how to reduce the need for superior working memory capacity.

3.3.6 Perceived attentional control and directed attention

Attentional control helps to avoid distraction and is, therefore, critical to supporting multi-tasking. Few multi-UAS control studies address participants' perceived attentional control (PAC). The reviewed literature showed that participants with higher PAC measured using tests, such as the Attentional Control Survey [67], exhibited better overall multi-tasking performance.

Participants using autonomy with low reliability, who also had low attentional control, appeared to be unable to allocate as much attention to all parts of the tasking environment [7]. While performing an automated route editing task, participants with high PAC outperformed those with lower PAC during the low reliability miss prone autonomy condition. This result may indicate differences in the ability to detect changes, a topic addressed by Kidwell, Calhoun, Ruff and Parasuraman [44], Riggs and Sarter (2016) [27], and Riggs and Sarter (2019) [21].

A study that incorporated differing levels of autonomy when managing a three-vehicle convoy found that participants with lower attentional control experienced higher perceived workload than those with higher attentional control [26]. The lower attentional control participants also exhibited a liberal response bias in the target detection task, perhaps compensating for being overloaded. This interaction of individual differences and individual decision strategies/response bias warrants investigation.

The over-use of autonomy in supervisory control systems can induce boredom, thus, Mkrtchyan, Macbeth, Solovey, Ryan, and Cummings [46] investigated cyclical attention switching strategies in low task load scenarios. This study determined that boredom proneness [68] was not a major factor affecting participants' performance. However, an intervention with alerts and task switching was developed. The interventions supported sustain directed attention when an operator is controlling multiple UASs. However, while the alerts were found to support distracted operators for a considerable amount of time, they may be unable to sustain directed attention in operators for prolonged periods. This result may impact control station design and help to characterize the need for personalized alerting schemes.

There are well known issues associated with divided attention. Thus, the multi-UAS control station requirements need to consider specification of information elements. Further, the recommended design guidance needs to address attentional demand to ensure that it does not overburden this cognitive system.

3.3.7 Vigilance

Vigilance (i.e., the need to focus attention over prolonged periods of time), and associated vigilance decrements (i.e., any performance decline due to having to complete a task over time) are important topics with regard to supervisory control tasks. Fatigue, one of the causes of vigilance decrements, has been an issue in aviation for traditional manned pilots and UAS crew members for decades [69–72]. High levels of fatigue can lead to task disengagement in addition to vigilance decrements. The introduction of autonomy can impact fatigue, as evidenced by Neubauer and colleagues' findings with driving tasks [73]. The required autonomy necessary for multi-UAS control will likely have direct implications on operator fatigue and vigilance decrements.

Recent studies that aimed to examine sustained performance and fatigue in multi-UAS tasks required participants to maintain performance for more than thirty minutes [24, 25]. The vigilance decrements were greater for a more difficult surveillance (vigilance) task, especially when the autonomy was less reliable. However, with low reliability, participants' performance was stable for close to 45 minutes. Performance recovered near the end of the two-hour session, perhaps due to a motivational factor of anticipating the end of the experimental session. The delayed onset of the vigilance decrement is promising for UAS surveillance tasks and needs to replicated in a more ecologically valid environment.

Managing vigilance and fatigue levels represent important factors in the design of multi-UAS control stations, and the scheduling of operators.

3.3.8 Stress

Prolonged performance of demanding vigilance tasks is hypothesized to tap attentional resources leading to an increase in extreme stress, or distress [74]. Distress may lead operators to rely more on decision support tools and related autonomy. Thus, researchers have investigated how stress can impact supervisory control of multiple UAS.

Participants engaged with a multi-task UAS simulation where two surveillance tasks were of higher priority and supported by autonomy [15]. Higher task demands impaired participants' surveillance task accuracy, increased neglect, while elevating stress and perceived workload. High demands increased task engagement in conscientious participants, and yielded higher correlations between stress and lower task accuracy as well as between task engagement and lower neglect. Distress correlated negatively with dependence on autonomy, perhaps because integrating the autonomy's recommendation created an additional task demand [75]. Neuroticism was positively correlated with distress, where those with higher neuroticism achieved higher accuracy for the more demanding surveillance task while under high task demand.

Two evaluations investigated the relationship between dispositional worry, metacognition, resilience, and stress responses when operating multiple UASs for reconnaissance and surveillance tasks [41] [16]. Traits associated with resilience predicted subjective and physiological responses to negative feedback and cognitive demand stressors in a simulation with two and six UASs. Worry traits, such as meta-worry, were generally associated with higher levels of situational stress, whereas hardiness and grit appeared to be protective. The Anxious Thoughts Inventory [76] measures were generally associated with higher state worry.

It is unclear how the impact of stress will change as the number of vehicles increases. These studies incorporated a very small number of vehicles, especially relative to the number of vehicles an operator is predicted to supervise in some domains, such as package delivery. The implications of multi-UAS task characteristics on operator stress will be important considerations for the development of effective UAS autonomy and control stations.

3.3.9 Resilience

There has been limited research with respect to psychological traits of perseverance for multi-UAS applications. It is unclear whether the various challenges of UAS operation and traits for resilience predict objective performance as well as subjective responses. A simulator-based study found that assessment and prediction of resilience may be useful for assessment in training programs and evaluation of fitness to cope with stress in the mission context [16]. The results showed that hardiness and grit correlated negatively with the Anxious Thoughts Inventory worry scales, which indicates that maladaptive metacognitive style may impair development of a resilient personality.

The literature lacks reliable and repeatable measures of resilience. The development of such measures is needed in order to better characterize what impacts resilience and can realistically be assessed, particularly in relation to the impacts on operator performance for multi-UAS systems.

3.3.10 Culture

As the UAS industry grows, operator demographics will likely shift to include a broader set of individuals from more diverse cultures. There have been few cross-cultural studies in the multi-UAS control domain. Chien and colleagues [28] investigated the effects of transparency, by culture, with respect to readiness to trust autonomy, and the degree of transparency required to use an autonomous path planner. Using participants from different cultures, the experiment varied transparency and the degree of autonomy, while assessing the willingness to use systems with high degrees of autonomy. Participants from a face culture (i.e., where one's dignity and prestige is derived in terms of one's social relationships [77]) exhibited bias by accepting recommendations from the autonomy, whereas those from dignity (i.e., one's self-worth is derived internally) and honor (i.e., self-worth is dependent on interactions with others and one's perception of self) cultures were less likely to trust or accept recommendations on this basis.

As more autonomy is incorporated into unmanned aircraft and their associated ground control stations, it is prudent to include participants from different cultures who may exhibit a range of responses with respect to autonomous system behaviors. Also, few training interventions exist that consider cross-cultural issues, which may be important for ensuring good training outcomes.

3.4 Training

The literature includes few studies focused on training for multi-UAS control. The need for additional research regarding redesigning training to accommodate new task requirements in the presence of increased autonomy has been noted [10]. The authors investigated the impact of including or removing control device training. The experimental design considered combinations of the presence or absence of unreliable automated target recognition (ATR) autonomy that assisted with imagery search tasks and skill-based training for using a trackball: a) Skill-based (trackball training) with ATR, b) Skill-based (trackball training) without ATR, and c) ATR without skill-based training. Participants with no ATR autonomy panned and zoomed more to find targets than those who used the ATR autonomy. Thus, the impact of the device training may manifest as a critical factor for operator performance. The lack of skill-based training with the control device did not affect the target search time. However, what device training needs to be required for autonomous, or partially autonomous tasks is an open question.

There is an increasing need for the FAA to standardize training requirements [78]; however, the only existing training knowledge requirements for single UAS control are specified in 14 CFR Part 107.73 [53]. Studies that investigate the trade-offs between training, additional autonomous capabilities for the UAS and in the control station, as well as fundamental control station design are warranted.

3.5 Mission and associated task characteristics

Researchers have considered missions and associated UAS tasks [79–90]. However, as described in the final ASSURE A10 project report for Tasks PC-1 through PC-3 [91], there are no common operational procedures for UAS pilots operating single UAS larger than 55 pounds. This finding is also true for multi-UAS control of small UAS. Original equipment manufacturers provide inconsistent operational procedures that are unique to their UAS.

A few common multi-UAS mission scenarios were identified: surveillance, reconnaissance, target detection/classification, and search. Kancler and Malek [92] interviewed subject matter experts (SMEs) that focused on intelligence, surveillance and reconnaissance missions in order to better understand current sUAS missions, capabilities, and expected payloads (e.g., sensor or weapon).

There is limited research focused on providing the operation with ground robot and UAS-based perspectives when controlling multi-UAS. However, some researchers have investigated soldiers controlling a suite of air and ground vehicles. Oron-Gilad and colleagues [39, 40] found that participants benefited from the detailed information provided by the ground vehicles. That is, the presence of the UAS imagery perspective alone was not as helpful for the operator and when the terrain was more open, the operators gained more information from adding the unmanned ground vehicle feed [39].

Future UAS tasks may require vehicles to transition from the NAS to indoor, non-NAS environments. Search tasks [42], such as for law enforcement, will require such NAS to non-NAS to NAS transitions. These transitions will impact the UAS' control and potentially communication link connectivity.

Most of the literature focused on missions composed of multiple tasks. For example, surveillance oriented missions often required the operator, often supported by autonomy, to allocate vehicle specific new imaging tasks, re-route vehicles in response to hazards or new task demands, as well as conduct image analysis and target detection. Some tasks, such as monitoring and responding to chat, were manual. The UAS completed some tasks independently in many cases, but in other cases, the operator and UAS were required to coordinate [93].

The research to date is helpful, but there is no comprehensive set of task analyses that have been conducted in order to support and better understand the demands of multi-UAS missions. The interplay of the number of aircraft, the range of tasks, and the type of autonomy and decision support need to be addressed and considered in a holistic manner.

3.6 System architecture and aircraft characteristics

The FAA develops system architecture and aircraft related regulations to ensure public safety and the safety and efficiency of the United State's national airspace. For example, the final remote identification of unmanned aircraft rule [94] recently modified the 14 CFR §107 rule and the final rule for operation of sUAS over people [95] recently modified the 14 CFR Part 107 requirements by including provisions for operations at night. These final rules mandated equipment, UAS design and production, and other requirements relevant to system architecture and aircraft characteristics. Similarly, additional system and aircraft related regulations may also be required for multi-UAS operations.

Most of the reviewed HITLs used simulations that did not model realistic aircraft control and dynamics, nor did they include algorithms and displays validated in field studies. The one exception is provided by Clare, Cummings, and Repenning [9]. The on-board planning system for unmanned vehicles Supporting Expeditionary Reconnaissance and Surveillance [96] was the computer simulation. These decision support displays allowed participants to operate small unmanned air and ground vehicles in real time [97].

The predominate simulation based evaluations do not provide high degrees of ecological validity and the necessary generalizability needed for real world multi-UAS applications. The aircraft, the control stations, the associated autonomous capabilities, and the environments have been idealized.

3.7 Aircraft group characteristics

CFR 14 Part 107 does not restrict the types of sUAS an individual can fly. Multi-UAS systems may be composed of homogeneous vehicles or may be heterogeneous. Heterogeneous multi-UAS systems may incorporate combinations of fixed winged and multi-rotor UAS models, UAS with differing sensor and actuator payloads, as well as combinations of propulsion types from different manufacturers. Heterogeneous systems, irrespective of aircraft performance may add significant additional complexity to the operator's tasks.

The simulated vehicle types in the reviewed HITLs included single UAS, homogeneous groups of UASs, unmanned ground vehicle systems, computer agents, simulated spaceships groups, as well as heterogeneous groups composed of three different vehicle types (one study used a UAS, unmanned ground vehicle and manned ground vehicle, while another incorporated a humanoid robot, sUAS and an unmanned ground vehicle), and an unmanned ground vehicle and UAS pair. The group sizes span from 2 to 20 vehicles. Some of the studies did not address the unmanned systems control, but rather focused on their video feeds.

Seven manuscripts included explicit changes to the number of agents supervised, either between trials or during a trial. Moacdieh, Devlin, Jundi, and Riggs [19] studied the effects of workload transitions that were gradual and sudden. Participants simultaneously controlled and managed three to five UASs, 13-16 UASs, or a number of UASs that transitioned between the lower and higher group sizes. The response time during the target detection task was shorter and detection accuracy was higher with the lower number (3-5) of UASs.

Operator performance for two adaptable autonomy configurations was evaluated by requiring participants to control one, two, three or four ground robots in a search and exploration mission [55]. The control modes were teleoperation, shared-control (operator sets a target point that the robot tries to reach it autonomously), and full autonomy (robot navigates autonomously, trying to maximize the explored area). The participants tended to use different control modes when supervising different numbers of robots. Participants almost always used the teleoperation mode when working with one robot, but relied primarily on shared control and sending parameters sequentially when working with three or four unmanned ground vehicles. Better mission performance was achieved with three robots.

Chen and Barnes [7] manipulated the number of ground robots (four and eight robots) in order to understand the effects of autonomy reliability (false alarm vs. miss prone) on multitasking performance. Participants detected fewer targets, had poorer SA, and reported higher perceived workload when completing the tasks with eight robots compared with four.

During the miss prone condition, participants had lower detection rates, but better situation awareness scores, than during the false-alarm prone condition. The latter result was due to more frequent map scanning during the miss prone condition.

The effects of autonomy reliability and adaptive autonomy on human-system performance for different taskload levels were examined [11]. Participants supervised heterogeneous groups: a) two experimental unmanned vehicles and one UAS or b) four experimental unmanned vehicles and two UASs. Autonomy reliability varied from 30% (low) to 70% (medium) to 100% (high) during the autonomous target recognition (ATR) task. A significant interaction existed between reliability and taskload. During the medium reliability condition, target detections increased as taskload increased, but detections decreased as taskload increased when using the low reliability ATR. An important finding is that taskload, or span of control, can be influenced due to other factors, not simply the number of UASs. These other factors can include mission type, task difficulty task-to-robot ratio, and autonomy reliability.

It was infeasible to make inferences about the number of vehicles for two evaluations in the multi-vehicle domain, because other parameters changed with the number of vehicles. Panganiban and Matthews [41] investigated whether measures (inhibition, switching, and updating) of executive functioning predict UAS operator performance and subjective state under stress in a simulated multi-UAS task environment. There were either a) 3 UASs, 8 hazards, randomly expiring initial targets (between 60-90 seconds), and new targets that expired after 60 seconds or b) there were 6 UASs, 14 hazards, and short target expiration times, 45-60 seconds for initial targets and 45 second for subsequent targets. Command Ratio appeared sensitive to individual differences in executive functioning. An additional evaluation investigated the relationship between dispositional worry, metacognition, resilience, and stress responses when operating multiple UASs for reconnaissance and surveillance [16]. Using a similar design, there were either a) two UASs, 9 hazards, 14 targets, targets that expired after 60 seconds, and hazards that expired after 5 seconds or b) there were 6 UASs, 14 hazards, 18 targets, targets (45 seconds expiration), and hazards (5 seconds expiration). Higher taskload significantly increased distress, situational uncontrollability, and subjective workload).

A varying number of cyber assets were used to investigate human performance and cognitive outcomes [45]. Participants controlled 4, 8, 12 or 16 computer agents using a set of commands, to monitor the progress and state of varying missions, and communicate with a mission commander to obtain permission to execute restricted commands. Participants struggled with the task independent of the number of agents, including the lowest level, 4. It is unclear if a performance increase with a smaller number of agents exists, given the evaluation design.

These evaluations demonstrate that researchers tend to not systematically investigate varying the number of UASs. Additionally, few evaluations systematically investigate the effect of a mixed fleet of sUAS. The reviewed manuscripts make clear the importance of studying group size in the context of other factors.

3.8 Autonomy, human-autonomy teams, and human-autonomy interaction

Researchers have studied crew and staffing requirements in unmanned operations, but less so with respect to envisioned multi-UAS applications and related UAS autonomy [98]. It is noted that 14 CFR Part 107 mentions operator roles, such as the remote pilot and "the person manipulating the flight controls of the small UAS,", but these roles are not inclusive of all the anticipated operator roles for multi-UAS control. Multi-UAS systems that incorporate more than a very small number of UAS will necessarily incorporate greater use of autonomous flight control and navigation and higher levels of autonomy. The remote pilot will serve in a more supervisory role. As such, "the person manipulating the flight controls of the small UAS" will either be a) the remote pilot, b) the autonomy, or c) both. For example, sUAS flying in close proximity may employ cooperative methods to maintain separation autonomously without human oversight.

While there is a significant body of research addressing different autonomous functions, associated level of autonomy, and human-autonomy related measures (see for example [33, 47, 51, 75, 99–131]), there are currently few manuscripts that specifically address multi-UAS control.

3.8.1 Human-robot team configuration

The overall organization and composition of the human-multi UAS team will be an important consideration for pilot proficiency requirements [132]. The span of more traditional human-robot interaction roles, from teleoperator to supervisor, will have to be considered for multi-UAS system integration into the national airspace. Further, new roles are likely to arise that will be domain specific or domain agnostic.

An important consideration for multi-UAS systems will be a question of whether the assignment of UAS operators to operational tasks will be fixed, or whether such responsibilities change based on scheduling or other contexts. A team-based approach to multi-UAS control using a shared pool of operators, based on call centers, was investigated [13, 32]. The approach incorporated a queue to allocate vehicles to a shared pool of operators. The hypothesis was that this approach better used operators and managed workload; however, this strategy did not provide performance benefits over a dedicated assignment of operators. The assigned-robot condition operators planned paths and controlled 12 robots each. The diffusion of responsibility for the shared operator pool actually led to performance decrements. For example, when robots were not clearly addressed by one operator, the another did not automatically supervise it. It appears that multi-UAS systems that incorporate teams of operators require more specifically constrained roles and responsibilities.

This work elucidates the need to investigate assignment strategies as well as the necessary procedures and training when selecting UAS to operator assignment methodologies, especially if the assignments vary with time or task demand. Unlike queueing models with independent tasks, this work shows that explicit mechanisms for assigning robots to operators are needed.

While the human-robot interaction community has continued to develop metrics, some specific to assessing human to robot ratios [132], there are no concrete algorithms or formulates that accurately predict that ratio by capturing the complexity of systems, the contingencies that can arise across, and the levels of autonomy. However, the literature demonstrates that given certain scenarios and control capabilities, operators were able to control approximately 10 robots in a simulated first response environment [133]. The shared operator pool condition, where operators were added without assigning robots, had fewer (8) robots controlled, on average. This decrement was attributed to diffusion of responsibility, a cost of human-to-human coordination. Viewed from a broader perspective, none of this prior research supports claims as to a safe operator-to-UAS ratio, regardless of whether the assignment of UAS to operators is fixed or flexible.

3.8.2 Autonomy

Supervisory control of multi-UAS systems requires autonomy. Many of the HITLs focused on the use of different forms and mixes of information analysis, decision alternative generation, decision selection, and decision execution autonomy integrated into the control station to support the operator's tasks. There has been less emphasis on the aircraft's required autonomy.

Some of the HITLs focus on what level of autonomy is needed to support each task. Research questions consider whether the level of autonomy (LOA) is static or flexible. If the LOA is flexible, then the research questions consider whether the operator controls of the autonomy change, or are *adaptable* (e.g., [51]), or whether the system changes the level based on context, such as operator taskload or performance, which is referred to as *adaptive autonomy* (e.g., [29]). In other words, adaptable autonomy allows the user to tailor the level of autonomy, while adaptive autonomy uses parameters, such as the operator's performance or other context to change the autonomy level.

For adaptive autonomy, design considerations then come into play because the threshold for adaptivity must be set accurately to determine how best to balance workload and performance [6].

An operator's ability to detect changes in the system state is critical. The act of delegating LOAs may improve situation awareness, especially with regard to unexpected events. While change blindness may be mitigated by interventions (e.g., [21]) focusing the operator directly on system operations may better support performance.

Calhoun, Ruff, Behymer, and Frost present design considerations and an interface paradigm for supporting human-autonomy teaming for air, ground, and surface UVs that support UV management using an adaptable autonomy control scheme [134]. The Playbook® concept supports human-autonomy communication and teaming by developing generalized plays representing more complex actions, inclusive of execution instructions (e.g., asset allocation, and routing) that an operator can issue as is (i.e., default parameters) or can customize to the current situation [135–137]. The design processes included ecological interface design constructs, and generation of UV and task-related pictorial symbology (e.g., [3] and [17]).

Predefined autonomous robot behaviors are often brittle [18], which is an important consideration for the delegation-based control provided by the Playbook®. Plays are defined based on expected deployment conditions using default parameters, since uncertain environments will present unanticipated conditions. The operator can adjust the plays' parameters to customize the play as needed [136]. Supporting the plays demands that some action and decision-making autonomy be delegated to intelligent subordinates. However, circumstances will arise for which the plays are not applicable, such circumstances are "non-optimal play environments" (NOPEs), the operator must abandon play usage and rely on more primitive behavior commanding. The autonomy appeared to free cognitive resources during routine events, which may have improved situation awareness to support non-routine circumstances. The delegation-based control (play calling and adaptable autonomy) holds promise for multi-UAS control, and may even provide benefits for cases when predefined plays do not exist.

Another set of research questions addressed LOA across synchronous and sequential tasks. Specifically, the LOA for concurrent tasks and sequential tasks needs to be considered as a joint design decision, as demonstrated via an investigation in which operators controlled three UAS [5]. The performance on both the primary tasks and many secondary tasks was better when the LOA was the same across the two sequential primary tasks, which implies that the LOA needs to be similar across closely coupled tasks in order to reduce mode awareness problems.

The literature review did not identify results that systematically automate the full range of activities that the operator must attend to within multi-UAS systems. However, this finding is understandable given the breadth of UAS systems, their capabilities, and the complexity of multi-UAS systems with regard to size, task domains, and applications.

3.8.3 Reliable Autonomy and Trust in Autonomy

The reliability of autonomous systems has been a topic of general research for over a decade. Many of the questions related to validation and verification of autonomous systems are left unanswered and directly impact UAS systems. Perceived reliability of autonomy, and the subsequent trust placed in these autonomous systems, seems particularly important given the need for autonomy to manage the high task demands of managing multi-UAS systems.

One concern is whether operators will even use less than perfect autonomy. A supervisory route planning task was used to evaluate operator compliance and reliance [48]. The results found relatively high compliance (above 60% and below 80%) and reliance rates (between 60% and 70%). Algorithms that generated paths similar to previous paths developed by the participant resulted in the highest compliance and reliance rates, while the lowest rates were recorded for paths that were very different from the participant generated paths. Hussein and colleagues [12] examined whether autonomy reliability or transparency can influence human reliance behavior (i.e., reliance rate and proper reliance) and mission performance. These scenarios required supervising 20 UASs executing image retrieval and object identification tasks. It was found that enhanced reliability of a supervisory control decision aid led to enhanced overall accuracy, but also increased human complacency and overtrust. Similarly, when using robots to detect information [8], lower system reliability resulted in operators making more camera selections, indicating that an unreliable system led to more active supervision of robot status and system performance. Naturally, this additional supervision provided increased detection opportunities, but also had the unfortunate consequence of increasing operator workload, which may also impact trust in autonomous systems.

Indeed, it has been found that taskload can interact with the degree of autonomy to impact trust. Prinet, Terhune, and Sarter [20] compared re-planning and target detection performance in multi-UAS control that incorporated video feeds from 9 UASs. The re-planning task was evaluated at three LOAs (manual, intermediate, full) where the autonomy was not perfectly reliable due to missing information, called partial observability. Re-planning and target detection performance was evaluated in low and high taskload conditions. The fully autonomous re-planning aid resulted in the fastest completion time and re-planning score, although the intermediate LOA was equivalent in terms of target detection. However, re-planning scores for the two autonomous conditions were highest when the taskload was also high. During the high workload conditions, operators over-relied on the autonomy by choosing the first, or only option, without careful review. As such, more than half the participants trusted the manual mode most, and placed the intermediate mode third. The effects of task sequencing on workload, with differing LOAs, has also been investigated [5]. An early sequence of autonomous tasks may be favored by operators and free them to focus on subsequent tasks. However, unreliable autonomy can also increase the operator workload required to monitor the autonomous behaviors, which can far outweigh any performance benefits. This finding suggests that design aids for facilitating operator monitoring of autonomous decisions are warranted.

Operator preferences for autonomy may also need to be considered when choosing a LOA. For example, participants who play computer and video games frequently had a higher propensity to overtrust autonomy [9], and a context-sensitive approach to choosing the LOA may realize the benefits of autonomy while avoiding its potential costs. Trust was manipulated in an evaluation during which participants guided an automated scheduler to create, modify and approve schedules for a team of UAS using positive priming, negative priming, or no comments about the automated scheduler [9]. Participants with computer and video game experience tended to overtrust the automated scheduler and when exposed to a positive priming intervention, they had fewer interactions to engage the autonomy. Priming gamers to lower their initial trust to a more appropriate level, the system performance improved by 10%, as compared to that of gamers who were primed to have higher trust in the autonomy. These results have implications for training as well as for personnel selection for supervisory control of multi-UAS. Priming during training and operations may help to overcome overtrust of autonomy.

The research suggests that placing operators in what are perceived to be either highly demanding or highly reliable autonomous situations can led to overtrust in these autonomous systems, which may negatively impact the ability of personnel to monitor and intervene in task duties when necessary. Conversely, unreliable systems lead to lower levels of trust, but often are accompanied with heightened levels of perceived workload to compensate for the unreliable autonomy. Trust in autonomy, particularly over or under trust is very important in multi-UAS deployments. Overtrust in various domains has shown that people are out-of-the-loop and frequently unable to respond appropriately or quickly to incidents and off-nominal conditions from which the vehicle or system is unable to autonomously recover. At the other end of the spectrum is undertrust, which often results in operators micro-managing systems in ways that can lead to incidents.

3.9 Control station standards and guidelines

The final reports for Project A7 [138] and Project A10 [139], Tasks CS-1 through CS-5 indicate a need to develop recommendations for minimum UAS control station standards and guidelines for single UAS systems. This need also exists for multi-UAS control; however, it may be significantly more difficult to do so given broad differences in future multi-UAS capabilities and applications.

3.9.1 Information elements

The multi-UAS operational concept assumes the UAS provided information will be presented at the control station. Thus, defining what information is to be available to the remote pilot is critical.

3.9.1.1 Minimum information requirements

Different efforts are developing information requirements for UAS control. Projects A7 [138] and A10 [139] as well as others [84] provided minimum information requirements for UAS tasks when controlling a single larger UAS. UAS detect and avoid (DAA) operations represent one of the more common autonomous behaviors. SC-228 adopted a quantitative definition of "well clear" and developed alerting criteria for DAA encounters and UAS pilot interaction with DAA systems [89]. Human subjects evaluations have focused on identifying minimum DAA information requirements, maneuver guidance, and display design recommendations for single UAS (e.g., [140–143]). However, there have been no comprehensive studies addressing the minimum information requirements for controlling multi-UAS.

3.9.1.2 Transparency

Transparency is an important factor for controllability by humans of autonomous systems and can potentially mitigate some of the issues with less than perfect autonomy. The Situation Awareness-based Agent Transparency model, see Figure 1, supports human awareness in human-agent teams [144]. The situation-awareness-based agent transparency model, originally designed for single robot systems, is useful for facilitating shared understanding and calibration of trust in human-multiple robot teams.

Transparency plays a key role in mission performance, situation awareness, usability, trust development, correct acceptance and rejection rates, response time, efficiency and reliance. A summary of the effects of the systems reliability and transparency on the human are provided in Table 4.

The task context specific mechanisms that support transparency benefits remain under investigation. For example Mercado, Rupp, Chen, Barnes, Barber and Procci [33] investigated a planning task in order to examine the level of information necessary to create an effective and transparent interface to support a human teaming with multiple unmanned experimental vehicles. Incorporating reasoning and uncertainty information into heterogeneous tactical decision making helped the participants to make better-calibrated decisions.

The impacts on the operator's workload of varying the transparency of an agent' reasoning were examined [35]. This evaluation also investigated how differing measures of workload

Situation Awareness-based Agent Transparency

Level 1: Goals & Actions

Agent's current status/actions/plans

- Purpose: Desire (Goal selection)
- Process: Intentions (Planning/Execution); Progress
- Performance
- Perception (Environment/Teammates)

Level 2: Reasoning

Agent's reasoning process

- Reasoning process (Belief/Purpose)
- Motivations
    - Environmental & other constraints/affordances

Level 3: Projections

Agent's projections/predictions; uncertainty

- Projection of future outcomes
- Uncertainty and potential limitations; Likelihood of success/failure
- History of Performance

Figure 1: Situation awareness-based agent transparency model, adapted from [145]

compared in assessing and understanding cognitive workload. While this work addressed convoy management, access to agent reasoning did not increase overall operator performance and workload. However, a comparison of the individual factor ratings to the workload measures found differences in participant behavior between transparency levels.

Transparency is a nascent topic, particularly in relation to multi-vehicle systems. Many open questions remain, including how much transparency is necessary to support multi-UAS deployments, what is the minimum necessary for safe operation, and can there be too much transparency?

Table 4: Effects of reliability and transparency on human reliance behavior and overall performance

Response variable	Impact of reliability	Impact of transparency
Reliance rate	Increases [12]	No effect [12]
Proper reliance	Increases (correct rejection) [12]	Increases [12, 33, 146]
Mission performance	Increases [12]	No effect [12]
Efficiency	No effect [12]	No effect [33, 147]

3.9.1.3 Camera video data

An operator working with multi-UAS can easily become overloaded with multiple sensor inputs. A common sensor feed is visual information, but future systems are expected to include traditional robotics sensors (e.g., LiDAR) and new sensors (e.g., package weight or secure package stowage). Pilots of single UAS often view a provided video feed, however, it is unclear how to scale this type of imagery for multi-UAS systems. A critical issue occurs when the operator is using views from multiple UASs and needs to integrate the information to generate a common understanding or operational picture. Control station design strategies range from co-locating video feeds in different ways on the same workstation, to providing display augmentation, to easing the transition from one video feed to another, to developing integrated synthetic camera views.

Oron-Gilad and colleagues [40] investigated display support, but found that using a single window that toggled through the imagery was too slow for the pace of task demands in a dynamic operational context. Split views (two equal sized views) and combination screens (one larger and one smaller) were rated as more optimal compared to single screen displays. The combination layout provided an operational advantage over the split screen, as it can potentially be expanded to include more than one "small window" in the layout. However, the scalability of this approach will only be applicable to some multi-UAS system domains that contain a small number of vehicles, or have the capacity to integrate very large workstations.

Supporting an operator's understand of how different camera images are spatially related to one another was addressed in a display concept that transitioned between camera views when multiple UASs were monitoring the same object/scene [4]. While this work focused on higher altitude flight operations than what is in scope for A26, the simulation-based experimental results demonstrate the benefits of such tools to support transition aids.

Often algorithms are developed to process sensory inputs, but the implications of the algorithm's outcomes on operator performance are often not understood. The algorithm design of system augmentations intended to support operator performance were investigated previously [38]. An automatic target recognition system with an additional cue (a box was drawn in the region in which a possible target was detected) was expected to reduce workload and improve overall performance. However, the results indicated that the system impacted response bias. The underlying algorithm pulled images from an area, based on target detection priority and coverage. which may have attributed to this outcome in which operators monitored the same area.

Many have investigated algorithms that integrated multiple camera views, or even multiple images from the same camera into a cohesive display. Abedin and colleagues [2] developed an integrated synthetic view from multiple independent camera feeds. However, the researchers did not address any latency with respect to creating the 3D model and there was no consideration of the impact of potential latency in representing synthetic data to the operator in near real-time. Depending on the latency duration, there are domains for which the impact can be minimal, but in others, any latency will hinder the operator's ability to respond appropriately.

An important issue to be addressed for multi-UAS control relates to the role for video/image feeds. There has been no comprehensive study to address when imagery is absolutely necessary. It is possible that vendors may wish to supply imagery for operators' benefit, but the notion of whether imagery must be available has yet to be proven. Understanding the necessity of imagery is crucial, since the computational and communication loads associated with imagery from mult-UAS systems will likely be very high.

3.9.2 Input devices

Most of the single UAS control devices support direct teleoperation, as well as graphical user interfaces with keyboard and mouse inputs. For multi-UAS control, the majority of the HITLs included graphical user interfaces with keyboard and mouse inputs that allowed the operator to supervise all of the vehicles from the same set of windows. Some research has addressed multi-modal interfaces, such as tactile interfaces [20, 21].

Multi-robot teleoperation schemes based on traditional personal computer (e.g., keyboard and mouse) and game console input hardware (e.g., video game controller) were compared for a 3D spatial interaction interface [52]. While the keyboard scheme exhibited shorter completion times and fewer errors, no significant differences were found for performance measures by input device.

Different researchers have tried to develop better control station designs to support multi-UAS operations. However, no research has addressed the question of what are the minimum device input requirements. More complex the work station and the input devices will create a greater barrier to entry and increase the need for subsequent training.

3.9.3 Display design

Researchers have been investigating display configurations to support UAS operations. For example, several studies have addressed UAS pilot DAA alerting requirements and display designs that incorporate conflict detection, resolution and execution tools (e.g., [140–142, 148–152]).

The use of mission-coded map icons to assist operators when making decisions were investigated for play-based interfaces and multiple UASs [3]. Presenting pictorial icons that represented different base defense events directly on the map reduced the time required to locate these mission relevant events. The map icons supported situation awareness, and may support better decision making for multiple UAS control.

Many open questions exist for how best to display very large multiple-vehicle systems, or swarms. Five swarm visualizations, some that displayed all individual vehicles and some that abstracted away individual vehicles, were analyzed for two common multi-UAS tasks (e.g., go to a goal location and detection and avoidance of obstacles [22]). The video-based evaluation investigated how the visualizations impacted human ability to identify the swarm's current task, goto or avoid, when the visualizations either included or excluded the obstacles. The three visualizations that incorporated individual agents resulted in the highest accurate recognition of the swarm's current task, while one of the abstract visualizations provided similar, but lower detection accuracy. Future work needs to investigate the relationship between tasks and the best visualizations, since results have shown that humans perceive biological swarm movements as a complete entity, rather than the individuals.

Change blindness occurs when people fail to detect even large changes in a visual scene or on a display, when these changes coincide with another visual or transient event [153]. However, crossmodal change blindness occurs when the individual does not detect differences across sensory modalities. The extent that, and when, crossmodal change blindness impact operator performance were investigated [21]. Specifically, this evaluation investigated touch's susceptibility to change blindness, and how global visual changes, including luminosity, impact visual change blindness, and if crossmodal change blindness occurs with the sensing modalities by manipulating tasks demands along with cue modality and transient modality type (i.e., cue-transient combination). The results demonstrated that change blindness is an issue for these multimodal displays and needs to be considered for future multimodal displays. There is a potential for training to mitigate the effects of crossmodal change blindness, but training was not incorporated into this evaluation.

While the research to date is useful, to ensure reliable and effective control displays, manufacturers will need explicit requirements in order to bring their systems to market. Manufacturers will need to know what these standards are as well as what standards are applicable to a given context.

4 Gaps

Many wish to focus on the single crew member in control of multiple UAS and the associated operator-to-vehicle ratio; however, that ratio is highly dependent on a broad set of factors, including the overall multi-UAS ecosystem (i.e., the physical infrastructure, hardware and software systems, and personnel) and aspects that are "hidden from view" when developing such systems for a given domain. This literature review has identified a number of unaddressed gaps. The most noteworthy gaps are summarized.

1. **Entity in control**: Who or what is ultimately in control of the UASs, either individual UAS or coordinating groups of UAS, in a multi-UAS system? Some multi-UAS systems will require very high levels of autonomy, autonomy that needs to handle a breadth of adverse events. As the complexity of the multi-UAS system increases, the human will be "on-the-loop" rather than "in-the-loop", as such the human will be ill-equipped to handle an adverse event. However, depending on the domain, operational environment, or adverse events, a human entity may be best equipped to be in control, or at least maintain some authority over the system's UAS components.

2. **Crew Roles**: What are the minimal crew role types necessary to support a multi-UAS system and what is the required proficiency of each role? The crew roles specified by 14 CFR Part 107 are not necessarily relevant in the multi-UAS domain. The common and well understood human-robot interaction domain roles, such as supervisor and mechanic (e.g., [132, 154]), are applicable, but there will be new crew roles that have not existed previously. For example, new domain uses (e.g., delivery drones) will introduce new crew roles that currently do not exist (e.g., load operator).

3. **Crew Composition** What are the allocations to the crew roles, more specifically, how many individual humans are required to staff each crew role? Some domains will have multiple individuals in a particular crew role (e.g., flight supervisor), but it is unclear how the ecosystem's UAS will be allocated across the individuals in a particular crew role. What are the minimal combination of crew roles and the staffing numbers associated with those roles? What are the criteria on which the crew composition is dependent (e.g., multi-UAS system composition, domain, task complexity)?

4. **Climate Conditions**: What are the implications of the effects of weather, or geographical or human built structure induced microclimates, on crew member responsibilities? This question needs to be answered from the perspective of the multi-UAS system capabilities and well as the role-based crew member responsibilities.

5. **Flight Phases**: Multi-UAS systems will have similar flight phases as single UAS operations (i.e., pre-flight, launch, take-off, climb to cruise, cruise, descent, approach, landing, recovery, post-flight). The crew role responsibilities and proficiency requirements for all flight phases, other than cruise, have not been investigated. Important issues include whether or not UAS to crew role assignments are based on flight phase, and if not, what are the implications on crew handling multiple UAS in different flight phases simultaneously? What are the adverse event flight phases and the associated implications on the crew roles?

6. **Altitude Maneuverability**: UAS have different morphologies (e.g., omni-directional multi-rotor or helicopters, fixed wing, or hybrid) that determine a particular vehicle's ability to hold a stationary position or navigate either laterally and vertically. As such, some UAS can navigate the airspace differently than manned aircraft. While these same capabilities are also available with single UAS systems, there are undetermined implications for the UAS morphologies within multi-UAS systems and the crew roles with regard to altitude and yaw control.

7. **Area of Operational Control**: Existing regulations related to the area of operation (i.e., restricted airspace or no fly zones) and geofence capabilities for single UAS will not necessarily translate to multi-UAS domains. The implications of the existing regulations on multi-UAS human roles is not entirely clear. Generally, the regulations can apply, but depending on domain, these operational criteria may be predefined "default settings" that change infrequently (e.g., delivery drones) or may require partial or full specification, such as a geofence, for other domains for which the area of operation cannot be prespecified (e.g., disaster response).

8. **Multi-UAS System Composition**: Multi-UAS systems in certain domains will be composed of 100% homogeneous (i.e., identical) UAS, where the system complexity will arise from the number of UAS and the mission complexity. However, Multi-UAS systems will also be composed of heterogeneous UAS, either in morphology, payload, or even larger capacity, but all other system aspects being identical. How does system composition impact the crew roles and team compositions? Do the minimal information requirements apply across vehicle heterogeneity, in order to standardize the crew stations? Are there UAS morphology or payload characteristics that the crew role and station must accommodate, and if so, how? Do heterogeneous system compositions require different crew role competencies and training?

9. **Mission Task Composition**: How do the crew station, crew proficiency and competencies as well as the minimal requirements differ between multi-UAS systems performing a set of standardizable tasks (e.g., drone delivery) versus highly dynamic, uncertain or unpredictable missions (e.g., disaster response)? Similarly, what are the implications of loosely coupled tasks (i.e., each UAS performs an independent task) versus tightly coupled tasks (i.e., multiple UAS conducted a highly collaborative task), as well as missions composed of tasks across the task coupling spectrum? How can unexpected or emergency operations, and task compositions (e.g., unique, previously unthought of disaster response task) be accommodated safely in situ by the crew?

10. **Communication Link Loss**: Communication link loss will be inevitable in some multi-UAS domains with standardized communication systems. What are the minimal requirements for a multi-UAS system to maintain a link to the crew? Does the Multi-UAS system, and hence the control stations have to accommodate intermittent lost link or allocate individual UAS to serve as ad hoc communication links? Do the UASs have to return to the coordinate of a last known link location before proceeding? If the UASs are capable of autonomously completing the task safely (i.e., a package delivery) do they do so and what information must be communicated to the crew? Does the

multi-UAS ecosystem require intelligent decision support to predict the likely actions of the UAS during lost link? These are just a few of the relevant questions.

11. **Airspace Transitions**: While it is noted that the FAA is focused on operations in the National Airspace (NAS), it is prudent to recognize that future multi-UAS domains will require aircraft to transition between the NAS and non-NAS (e.g., tunnels and building interiors). Domains, such as disaster response, will require UAS to enter non-NAS spaces (e.g., search and rescue and structural inspections after a hurricane). The key concern is handling the transitions between these airspaces, which often require an UAS to transition between flight control methods in order to safely perform its tasks. What are the responsibilities of the crew roles and the UAS platforms in these scenarios? What are the minimal requirements to ensure safe transitions between such airspaces and what specifically must the crew roles know from the UAS and be able to control? It will be difficult for crew to control this transition, and in some cases, to even approve this transition.

12. **Function Allocation**: How are the mission responsibilities allocated between the crew roles, individual crew members within a role, the individual UASs and the multi-UAS ecosystem? This allocation will depend on many factors (e.g., autonomy level, mission task composition, crew role). The function allocation will ultimately define responsibility for the various mission and system components that may encompass legal responsibilities, a topic excluded from this literature review.

13. **Autonomy**: Autonomy is a broad concept that can control an individual UAS, including responding to off-nominal and adverse events, but will also be incorporated into the broader multi-UAS ecosystem as intelligent processing and crew role specific decisions support. Fundamentally, autonomy is an aspect of artificial intelligence, which will be embedded into the ecosystem. The minimal UAS autonomy requirements and their implications on the multi-UAS system are not understood. What off-nominal and adverse events must be handled autonomously by the UAS to ensure safety and when does the UAS need assistance from a crew member or for that a crew member to assume control? Examples of the ecosystem autonomy include the ability to combine raw sensory information from multiple UAS into a crew accessible and meaningful operational picture, or the system planning the flight paths. While artificial intelligence is broader than machine learning, the fact is that future successful multi-UAS systems will adapt and learn from their experiences, which will also adapt and change the UAS' and ecosystem's autonomous capabilities. As such, the required minimal autonomy will have to consider a breadth of the provided gap factors and validation methods are necessary to continuously ensure sustainment of those minimal autonomy and safety requirements.

14. **Crew Role: Operation Station**: A breadth of crew role specific operation stations will be necessary to support the entire multi-UAS ecosystem; however, these operation stations will be difficult to regulate given vastly different domain and system specific core capabilities. What are the minimal requirements are that operation stations must incorporate and how do those requirements differ by crew role and various other system

and domain characteristics? Some domains will require crew roles, such as a delivery drone load operator, who may use a custom stationary or hand-held operation station, which differs from the pilot not flying located in a comfortable control room using an operation station with rich input and output peripherals. Similarly, a domain's operational conditions will influence the operation station. For example, a disaster response flight supervisor may be located in an emergency response vehicle using a laptop-based operation station with limited input and output peripherals.

(a) **Operation Station: Inputs**: The most reliable and accurate control and information specification modalities for multi-UAS systems are not fully understood, as they will vary based on crew role and domain. The multi-UAS ecosystem crew roles will require different information inputs and potentially input modalities. Broadly, what must be input and controlled is not well understood and will have to be allocated across the various crew roles. Domain characteristics will further influence what information is input by whom and when, but more importantly will influence the input peripherals and modalities (e.g., keyboard, joystick, natural language). What are the necessary crew role specific inputs? How do different input peripherals and modalities influence safety?

(b) **Operation Station: Outputs**: What is the minimal information required to complete the crew role responsibilities, which are expected to differ dramatically from single UAS deployments. How does the autonomy of the system's vehicles alter the information requirements? Do the information requirements change by flight phase or adverse event? How is the breadth of multi-UAS sensor information aggregated and integrated into a comprehensive, meaningful presentation from which unbiased, accurate decisions can be quickly derived and appropriate, necessary actions taken? If the UAS is the pilot in control, when must it notify the human pilot not flying of its status and via what means? A operation station with a video feed display for each vehicle will not be useful or usable in many domains; however, maintaining access to the live video feeds may represent a minimal information requirement. A human pilot not flying will be unable to maintain awareness of each vehicles' status via individual video relays. Further, what is the set of standardized symbology (e.g., Mil-STD-2525D map symbology) to be used to ensure a common operating picture across multi-UAS systems and domains?

15. **Crew: Trait Selection**: The different crew roles needed to support the multi-UAS ecosystem will require different fundamental human traits, and pre-screening for minimal basic traits needs to be considered. One such trait will be minimal level of education and demonstrated competency (e.g., high school diploma, trade skills). The traits for some crew roles require further investigation, such as the necessary level of inherent human performance capabilities (e.g., spatial awareness, reaction time, and ability to respond to stressful situations calmly). The minimal trait requirements are aspects required to increase the likelihood of successfully training and attaining a minimal level of competency relevant to the crew role in the multi-UAS ecosystem.

16. **Crew: Diversity**: Females are clearly under represented in the remote pilot certifica-

tions, and while not reported in the literature, it is believed that other diverse groups are under represented. However, developing the workforce for multi-UAS crew roles will require engaging all segments of the population, and not only individuals who possess certain backgrounds (e.g., gaming). As multi-UAS systems change businesses, there will be a growth in UAS crew role jobs and a decrease in others (i.e., delivery and ride share drivers). Developing and engaging interest, while keeping the barrier to entry accessible will be critical for developing a workforce.

17. **Crew: Training**: The minimal crew role traits will influence the minimal training requirements associated with each role. While the FAA ASSURE project A27 is developing a UAS pilot training framework for type certified UAS based on established industry UAS pilot standards, the characteristics of multi-UAS systems may differ significantly. As such, aspects of that framework may be leveraged for only a subset of crew roles in the multi-UAS ecosystem. However, training and certification requirements across the crew roles must be commiserate with the minimum level requirements related to the crew role's traits and focus on supporting the crew role's level of control, interaction and responsibilities with respect to the multi-UAS ecosystem (e.g., a delivery drone load operator requires less minimal training, perhaps two hours, than the pilot not flying, perhaps a few weeks). The recertification cycles and requirements will also be dependent on the crew role responsibilities. Further, some crew roles may require specialized training unrelated to UAS, such as regulatory compliance. Addressing personnel turnover will also be important, and potential career trajectories will be needed in order to retain a highly trained workforce.

18. **Crew: Competency Certification**: Validating crew role competency will encompass basic skills, and for some roles, fundamental human factors performance characteristics (e.g., workload, spatial awareness). Easily accessible minimal crew role specific competency (re)certification assessments must provide an accurate and objective validation of the skills and competencies. Skill degradation can occur for many reasons, including biologically oriented degradation (e.g., reaction time or spatial awareness). Subjective metrics dominate the literature evaluation analyses of human performance capacity; however, these metrics are insufficient for purposes of certifying competency and proficiency for multi-UAS crew roles. A minimal set of objective validation metrics capable of mitigating individual differences are required that accurately assesses all aspects of the minimal crew role specific competency requirements are met.

5 Conclusion

This literature review provided an insightful examination of the results of past research and identified large gaps in understanding. These gaps must be addressed before the FAA is able to lift the restrictions laid out in Part 107.205 and develop regulations and guidelines regarding multi-UAS operations. Based on these findings, the ASSURE team will begin to fill those gaps through modeling and case study validation. Within the review of previous work, the team found that most research was conducted around HITL and the human factor limitations for operating and monitoring multiple sUAS. These simulation-based evaluations used some objective performance measurements, like target detection rates and response times, and relied heavily on subjective measurements, like perceived workload, trust in automation, and situational awareness.

The initial gap findings can be summarized into five main gaps:

- Phases of Flight – It is well known in the aviation industry that takeoff and landing are the two most dangerous phases of flight. This literature review highlighted that very little research has focused on these flight phases, and the research has focused primarily on cruise flight. These critical phases, along with preflight, climb, decent, approach, recovery, and post-flight will need to be addressed.

- Crew Rolls – When developing crew rolls, one must consider the UAS ecosystem as a whole, potentially including an entire organization. Factors to consider include (1) there may be one operator in charge (e.g., a traditional pilot in control), or an entire crew organization, (2) how many humans are considered a part of a specific crew, and (3) what new roles need to be defined or introduced.

- Training – More focus is needed to define required training. Since the systems are becoming more automated, there is less need for months or weeks of training. Previous work looked at training considerations for Part 107 operators verses UAS degree programs. The future of UAS autonomy forces the ASSURE team to look closer at everyday citizens becoming operators and what that training needs to encompass.

- System Requirements – There is little research considering the type of system, which is broken down into two distinct groups, a single UAS or a multiple UAS structure. Factors that must be further investigated within the context of both definitions include, the maneuverability, weather, and system composition. The system composition can be further decomposed into how the system responds to communication link loss, transitions through airspace, and overall mission location (e.g., restricted airspace, or no fly zones).

- Autonomy – Although this gap falls under the system requirements gap, it drives the level of impact for most of the other gaps. The levels of autonomy will determine how many humans are needed, what training those humans will require, and what other system composition requirements will be necessary for safe flight.

The researchers will use this literature review and high-level gap findings to inform a deeper gap analysis. Based on the additional gap analysis, the research team will develop a model for a case study of drone package delivery. This loosely coupled tasks case study, where multiple vehicles conduct independent tasks, will provide a better understanding of what factors impact the human to UAS ratio for this particular domain. This model will investigate more broadly the complex relationship between the human and the UASs' level of autonomy. The team will evaluate a single case HITL, focusing on validating one aspect of the complex model.

The modeling and validation of the case study will illustrate how autonomy impacts the human to UAS ratio for the factors associated with package delivery and begin to answer the ultimate question; how many vehicles can one human control, and what performance standards must be developed to properly determine a safe human to UAS ratios based on level of autonomy of the aircraft.

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Bibliography

[1] "FAA Human Factors Policy Order 9550.8," 1993. https://www.faa.gov/documentLibrary/media/Order/9550.8.pdf.

[2] S. Abedin, M. Lewis, N. Brooks, S. Owens, P. Scerri, and K. Sycara, "SUAVE: Integrating UAV video using a 3D model," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 91–94, 2011.

[3] J. Bartik, H. Ruff, K. Behymer, E. Frost, G. Calhoun, S. Spriggs, and T. Hammack, "Mission-coded map icon decision aids for play-based multi-unmanned vehicle autonomy delegation," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, pp. 237–241, 2017.

[4] G. Calhoun, L. Warfield, N. Wright, S. Spriggs, and H. Ruff, "Automated aid evaluation for transitioning UAS camera views," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 413–417, 2010.

[5] G. L. Calhoun, H. A. Ruff, M. H. Draper, and E. J. Wright, "Automation-level transference effects in simulated multiple unmanned aerial vehicle control," *Journal of Cognitive Engineering and Decision Making*, vol. 5, no. 1, pp. 55–82, 2011.

[6] G. L. Calhoun, H. A. Ruff, S. Spriggs, and L. C. Murray, "Tailored performance-based adaptive levels of automation," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 413–417, 2012.

[7] J. Y. C. Chen and M. J. Barnes, "Supervisory control of multiple robots: Effects of imperfect automation and individual differences," *Human Factors*, vol. 54, no. 2, pp. 157–174, 2012.

[8] S.-Y. Chien, Y.-L. Lin, P.-J. Lee, S. Han, M. Lewis, and K. Sycara, "Attention allocation for human multi-robot control: Cognitive analysis based on behavior data and hidden states," *International Journal of Human-Computer Studies*, vol. 117, pp. 30–44, 2018.

[9] A. S. Clare, M. L. Cummings, and N. P. Repenning, "Influencing trust for human-automation collaborative scheduling of multiple unmanned vehicles," *Human Factors*, vol. 57, no. 7, pp. 1208–1218, 2015.

[10] M. Cummings, L. Huang, H. Zhu, D. Finkelstein, and R. Wei, "The impact of increasing autonomy on training requirements in a UAV supervisory control task," *Journal of Cognitive Engineering and Decision Making*, vol. 13, no. 4, pp. 295–309, 2019.

[11] E. de Visser and R. Parasuraman, "Adaptive aiding of human-robot teaming: Effects of imperfect automation on performance, trust, and workload," *Journal of Cognitive Engineering and Decision Making*, vol. 5, no. 2, pp. 209–231, 2011.

[12] A. Hussein, S. Elsawah, and H. A. Abbass, "The reliability and transparency bases of trust in human-swarm interaction: Principles and implications," *Ergonomics*, vol. 63, no. 9, pp. 1116–1132, 2020.

[13] P.-J. Lee, H. Wang, S.-Y. Chien, M. Lewis, P. Scerri, P. Velagapudi, K. Sycara, and B. Kane, "Teams for teams performance in multi-human/multi-robot teams," in

Proceedings of the Human Factors and Ergonomics Society Annual Meeting, vol. 54, pp. 438–442, SAGE Publications Sage CA: Los Angeles, CA, 2010.

[14] J. Lin, R. Wohleber, G. Matthews, P. Chiu, G. Calhoun, H. Ruff, and G. Funke, "Video game experience and gender as predictors of performance and stress during supervisory control of multiple unmanned aerial vehicles," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 746–750, 2015.

[15] J. Lin, G. Matthews, R. W. Wohleber, G. J. Funke, G. L. Calhoun, H. A. Ruff, J. Szalma, and P. Chiu, "Overload and automation-dependence in a multi-UAS simulation: Task demand and individual difference factors," *Journal of Experimental Psychology: Applied*, vol. 26, pp. 218–235, 2020.

[16] G. Matthews, A. R. Panganiban, A. Wells, R. W. Wohleber, and L. E. Reinerman-Jones, "Metacognition, hardiness, and grit as resilience factors in unmanned aerial systems (UAS) operations: a simulation study," *Frontiers in Psychology*, vol. 10, pp. 1–17, 2019.

[17] E. M. Mersch, K. J. Behymer, G. L. Calhoun, H. A. Ruff, and J. S. Dewey, "Game-based delegation interface design for unmanned vehicles: Color coding and icon row assignment," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, pp. 122–126, 2016.

[18] C. A. Miller, T. Shaw, A. Emfield, J. Hamell, E. deVisser, R. Parasuraman, and D. Musliner, "Delegating to automation: Performance, complacency and bias effects under non-optimal conditions," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 95–99, Sage Publications Sage CA: Los Angeles, CA, 2011.

[19] N. M. Moacdieh, S. P. Devlin, H. Jundi, and S. L. Riggs, "Effects of workload and workload transitions on attention allocation in a dual-task environment: Evidence from eye tracking metrics," *Journal of Cognitive Engineering and Decision Making*, vol. 14, no. 2, pp. 132–151, 2020.

[20] J. C. Prinet, A. Terhune, and N. B. Sarter, "Supporting dynamic re-planning in multiple UAV control: A comparison of 3 levels of automation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 423–427, SAGE Publications Sage CA: Los Angeles, CA, 2012.

[21] S. L. Riggs and N. Sarter, "Tactile, visual, and crossmodal visual-tactile change blindness: The effect of transient type and task demands," *Human Factors*, vol. 61, no. 1, pp. 5–24, 2019.

[22] K. A. Roundtree, M. D. Manning, and J. A. Adams, "Analysis of human-swarm visualizations," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, pp. 287–291, SAGE Publications, 2018.

[23] H. Ruff, G. Calhoun, E. Frost, K. Behymer, and J. Bartik, "Comparison of adaptive, adaptable, and hybrid automation for surveillance task completion in a multi-task environment," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, pp. 155–159, SAGE Publications Sage CA: Los Angeles, CA, 2018.

[24] R. W. Wohleber, G. L. Calhoun, G. J. Funke, H. Ruff, C.-Y. P. Chiu, J. Lin, and G. Matthews, "The impact of automation reliability and operator fatigue on performance and reliance," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, pp. 211–215, SAGE Publications Sage CA: Los Angeles, CA, 2016.

[25] R. W. Wohleber, G. Matthews, J. Lin, J. L. Szalma, G. L. Calhoun, G. J. Funke, C.-Y. P. Chiu, and R. Heath A, "Vigilance and automation dependence in operation of multiple unmanned aerial systems (UAS): a simulation study," *Human Factors*, vol. 61, no. 3, pp. 488–505, 2019.

[26] J. L. Wright, J. Y. C. Chen, and M. J. Barnes, "Human-automation interaction for multiple robot control: the effect of varying automation assistance and individual differences on operator performance," *Ergonomics*, vol. 61, no. 8, pp. 1033–1045, 2018.

[27] S. L. Riggs and N. Sarter, "The development and evaluation of countermeasures to tactile change blindness," *Human Factors*, vol. 58, no. 3, pp. 482–495, 2016.

[28] S. Chien, M. Lewis, K. Sycara, A. Kumru, and J. Liu, "Influence of culture, transparency, trust, and degree of automation on automation use," *IEEE Transactions on Human-Machine Systems*, vol. 50, no. 3, pp. 205–214, 2020.

[29] G. L. Calhoun, V. Ward, and H. A. Ruff, "Performance-based adaptive automation for supervisory control," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 2059–2063, 2011.

[30] T. Chen, D. Campbell, L. F. Gonzalez, and G. Coppin, "Increasing autonomy transparency through capability communication in multiple heterogeneous UAV management," in *2015 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, pp. 2434–2439, IEEE, 2015.

[31] E. de Visser, T. Shaw, A. Mohamed-Ameen, and R. Parasuraman, "Modeling human-automation team performance in networked systems: Individual differences in working memory count," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, pp. 1087–1091, SAGE Publications, 2010.

[32] M. Lewis, H. Wang, S. Y. Chien, P. Velagapudi, P. Scerri, and K. Sycara, "Process and performance in human-robot teams," *Journal of Cognitive Engineering and Decision Making*, vol. 5, no. 2, pp. 186–208, 2011.

[33] J. E. Mercado, M. A. Rupp, J. Y. C. Chen, M. J. Barnes, D. Barber, and K. Procci, "Intelligent agent transparency in human-agent teaming for multi-UxV management," *Human Factors*, vol. 58, no. 3, pp. 401–415, 2016.

[34] E. Rovira, A. Cross, E. Leitch, and C. Bonaceto, "Displaying contextual information reduces the costs of imperfect decision automation in rapid retasking of ISR assets," *Human Factors*, vol. 56, no. 6, pp. 1036–1049, 2014.

[35] J. L. Wright, J. Y. Chen, M. J. Barnes, and P. A. Hancock, "Agent reasoning transparency's effect on operator workload," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 60, pp. 249–253, SAGE Publications Sage CA: Los Angeles, CA, 2016.

[36] T. Zhang and J. A. Adams, "Evaluation of a geospatial annotation tool for unmanned vehicle specialist interface," *International Journal of Human-Computer Interaction*, vol. 28, no. 6, pp. 361–372, 2012.

[37] S. G. Hart and L. E. Staveland, "Development of NASA-TLX (Task Load Index): Results of empirical and theoretical research," *Advances in Psychology*, vol. 52, 1988.

[38] N. Brooks, P. Scerri, K. Sycara, H. Wang, S.-Y. Chien, and M. Lewis, "Asynchronous control with ATR for large robot teams," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 444–448, 2011.

[39] R. Ophir-Arbelle, T. Oron-Gilad, A. Borowsky, and Y. Parmet, "Is more information better? How dismounted soldiers use video feed from unmanned vehicles: Attention allocation and information extraction considerations," *Journal of Cognitive Engineering and Decision Making*, vol. 7, no. 1, pp. 26–48, 2013.

[40] T. Oron-Gilad and Y. Parmet, "Is more information better for dismounted soldiers? Display-layout considerations of multiple video feed from unmanned vehicles," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 345–349, SAGE Publications Sage CA: Los Angeles, CA, 2014.

[41] A. R. Panganiban and G. Matthews, "Executive functioning protects against stress in UAV simulation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 994–998, SAGE Publications, 2014.

[42] R. T. Stone, T. M. Schnieders, K. A. Push, S. Terry, M. Truong, I. Seshie, and K. Socha, "Human-robot interaction with drones and drone swarms in law enforcement clearing operations," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 63, pp. 1213–1217, 2019.

[43] J. L. Wright, S. A. Quinn, J. Y. Chen, and M. J. Barnes, "Individual differences in human-agent teaming: An analysis of workload and situation awareness through eye movements," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 1410–1414, SAGE Publications Sage CA: Los Angeles, CA, 2014.

[44] B. Kidwell, G. L. Calhoun, H. A. Ruff, and R. Parasuraman, "Adaptable and adaptive automation for supervisory control of multiple autonomous vehicles," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 428–432, 2012.

[45] V. F. Mancuso, G. J. Funke, A. J. Strang, and M. B. Eckold, "Capturing performance in cyber human supervisory control," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 317–321, 2015.

[46] A. A. Mkrtchyan, J. C. Macbeth, E. T. Solovey, J. C. Ryan, and M. L. Cummings, "Using variable-rate alerting to counter boredom in human supervisory control," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 1441–1445, 2012.

[47] J.-Y. Jian, A. M. Bisantz, and C. G. Drury, "Foundations for an empirically determined scale of trust in automated systems," *International Journal of Cognitive Ergonomics*, vol. 4, no. 1, pp. 53–71, 2000.

[48] J. G. Boubin, C. F. Rusnock, and J. M. Bindewald, "Quantifying compliance and reliance trust behaviors to influence trust in human-automation teams," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 61, pp. 750–754, 2017.

[49] M. R. Endsley, "Measurement of situation awareness in dynamic systems," *Human Factors*, vol. 37, no. 1, pp. 65–84, 1995.

[50] R. Taylor, S. Selcon, and A. Swinden, "Measurement of situational awareness and performance: A unitary SART index predicts performance on a simulated ATC task," *Human factors in aviation operations*, pp. 275–280, 1995.

[51] G. Calhoun, M. Draper, C. Miller, H. Ruff, C. Breeden, and J. Hamell, "Adaptable automation interface for multi-unmanned aerial systems control: Preliminary usability evaluation," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 57, pp. 26–30, 2013.

[52] S. L. Koh, K. Pfeil, and J. J. LaViola Jr, "Exploring the potential of full body and hand gesture teleoperation of robots inside heterogeneous human-robot teams," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 62, pp. 2008–2012, SAGE Publications Sage CA: Los Angeles, CA, 2018.

[53] "FAA Code of Federal Regulations (14 CFR) Part 107-Small Unmanned Aircraft System," 2016. https://www.ecfr.gov/cgi-bin/text-idx?node=pt14.2.107&rgn=div5.

[54] R. McKendrick, T. Shaw, H. Saqer, E. de Visser, and R. Parasuraman, "Team performance and communication within networked supervisory control human-machine systems," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 55, pp. 262–266, SAGE Publications Sage CA: Los Angeles, CA, 2011.

[55] A. Valero-Gomez, P. de la Puente, and M. Hernando, "Impact of two adjustable-autonomy models on the scalability of single-human/multiple-robot teams for exploration missions," *Human Factors*, vol. 53, no. 6, pp. 703–716, 2011.

[56] R. W. Wohleber, G. Matthews, L. E. Reinerman-Jones, A. R. Panganiban, and D. Scribner, "Individual differences in resilience and affective response during simulated UAV operations," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 751–755, SAGE Publications Sage CA: Los Angeles, CA, 2015.

[57] R. Schaufele and M. Lukacs, "FAA aerospace forecast: Fiscal years 2019–2039," tech. rep., U.S Department of Transportation (DOT) Federal Aviation Administration (FAA), 2019. https://www.faa.gov/data_research/aviation/aerospace_forecasts/media/FY2019-39_FAA_Aerospace_Forecast.pdf.

[58] "U.S. Civil Airmen Statistics," 2019. https://www.faa.gov/data_research/aviation_data_statistics/civil_airmen_statistics/.

[59] R. A. McKinley, L. K. McIntire, and M. A. Funke, "Operator selection for unmanned aerial systems: comparing video game players and pilots," *Aviation, Space, and Environmental Medicine*, vol. 82, no. 6, pp. 635–642, 2011.

[60] I. Spence and J. Feng, "Video games and spatial cognition," *Review of General Psychology*, vol. 14, no. 2, pp. 92–104, 2010.

[61] M. L. Bolton and E. J. Bass, "Comparing perceptual judgment and subjective measures of spatial awareness," *Applied Ergonomics*, vol. 40, no. 4, pp. 597–607, 2009.

[62] R. B. Ekstrom, J. W. French, and H. H. Harman, *Kit of factor-referenced cognitive tests*. Educational Testing Service, Princeton, NJ, 1976.

[63] L. Gugerty and J. Brooks, "Reference-frame misalignment and cardinal direction judgments: group differences and strategies.," *Journal of Experimental Psychology: Applied*, vol. 10, no. 2, pp. 75–88, 2004.

[64] A. D. Baddeley and G. Hitch, "Working memory," in *The psychology of learning and motivation: Advances in research and theory* (G. H. Bower, ed.), vol. 8, pp. 47–89, Academic Press, 1974.

[65] R. W. Engle, "Working memory capacity as executive attention," *Current Directions in Psychological Science*, vol. 11, no. 1, pp. 19–23, 2002.

[66] A. R. Conway, M. J. Kane, M. F. Bunting, D. Z. Hambrick, O. Wilhelm, and R. W. Engle, "Working memory span tasks: A methodological review and user's guide," *Psychonomic Bulletin & Review*, vol. 12, no. 5, pp. 769–786, 2005.

[67] D. Derryberry and M. A. Reed, "Anxiety-related attentional biases and their regulation by attentional control.," *Journal of Abnormal Psychology*, vol. 111, no. 2, pp. 225–236, 2002.

[68] R. Farmer and N. D. Sundberg, "Boredom proneness: The development and correlates of a new scale," *Journal of Personality Assessment*, vol. 50, no. 1, pp. 4–17, 1986.

[69] C. Cameron, "Fatigue problems in modern industry," *Ergonomics*, vol. 14, no. 6, pp. 713–720, 1971.

[70] S. D. Manning, C. E. Rash, P. A. Leduc, R. K. Noback, and J. McKeon, "The role of human causal factors in US Army unmanned aerial vehicle accidents," tech. rep., Army Aeromedical Research Lab Fort Rucker AL, 2004.

[71] M. R. Rosekind, P. H. Gander, D. L. Miller, K. B. Gregory, R. M. Smith, K. J. Weldon, E. L. Co, K. L. Mcnally, and J. V. Lebacqz, "Fatigue in operational settings: examples from the aviation environment," *Human Factors*, vol. 36, no. 2, pp. 327–338, 1994.

[72] A. P. Tvaryanas and G. D. MacPherson, "Fatigue in pilots of remotely piloted aircraft before and after shift work adjustment," *Aviation, Space, and Environmental Medicine*, vol. 80, no. 5, pp. 454–461, 2009.

[73] C. Neubauer, G. Matthews, L. Langheim, and D. Saxby, "Fatigue and voluntary utilization of automation in simulated driving," *Human factors*, vol. 54, no. 5, pp. 734–746, 2012.

[74] J. S. Warm, R. Parasuraman, and G. Matthews, "Vigilance requires hard mental work and is stressful," *Human Factors*, vol. 50, no. 3, pp. 433–441, 2008.

[75] E. J. Bass and A. R. Pritchett, "Human-automated judge learning: A methodology for examining human interaction with information analysis automation," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 38, no. 4, pp. 759–776, 2008.

[76] A. Wells, "A multi-dimensional measure of worry: Development and preliminary validation of the Anxious Thoughts Inventory," *Anxiety, Stress and Coping*, vol. 6, no. 4, pp. 289–299, 1994.

[77] W. Eberhard, *Guilt and Sin in Traditional China*. Berkeley: University of California Press, 1967.

[78] B. Torrence, B. Nelson, G. F. Thomas, B. L. Nesmith, and K. W. Williams, "Annotated Bibliography (1990-2019): Knowledge, Skills, and Tests for Unmanned Aircraft Systems (UAS) Air Carrier Operations," tech. rep., Cherokee Nation 3-S and Federal Aviation Administration, n.d.

[79] J. A. Adams, *Handbook of Unmanned Aerial Vehicles*, ch. 100 Cognitive task analysis for unmanned aerial system design, pp. 2425–2441. Springer Netherlands Dordrecht, 2015.

[80] J. A. Adams, C. M. Humphrey, M. A. Goodrich, J. L. Cooper, B. S. Morse, C. Engh, and N. Rasmussen, "Cognitive task analysis for developing unmanned aerial vehicle wilderness search support," *Journal of Cognitive Engineering and Decision Making*, vol. 3, no. 1, pp. 1–26, 2009.

[81] M. Askelson, H. Cathey, R. Marsh, Z. Waller, P. Snyder, G. Ullrich, C. Theisen, N. Kaabouch, W. Semke, M. Mullins, K. Foerster, R. Brothman, S. B. Hottman, K. Williamson, E. Johnson, A. VanHoudt, and Z. LaRue, "Small UAS Detect and Avoid Requirements necessary for Limited Beyond Visual Line of Sight (BVLOS) Operations," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), May 2017.

[82] P. W. Caro, "Aircraft simulators and pilot training," *Human Factors*, vol. 15, no. 6, pp. 502–509, 1973.

[83] R. M. Gagne, "Military training and principles of learning.," *American Psychologist*, vol. 17, no. 2, pp. 83–91, 1962.

[84] Alan Hobbs and Beth Lyall, "Human Factors Guidelines for Unmanned Aircraft System Ground Control Stations: Preliminary Guidelines 1.0," tech. rep., NASA, 2015.

[85] C. E. Nehme, J. W. Crandall, and M. Cummings, "An operator function taxonomy for unmanned aerial vehicle missions," in *12th International Command and Control Research and Technology Symposium*, pp. 19–21, 2007.

[86] C. Pankok Jr and E. J. Bass, "Information content requirements for remote pilot handover of control of unmanned aircraft systems in the National Airspace," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, pp. 81–85, SAGE Publications, 2018.

[87] T. B. Roby and J. T. Lanzetta, "Considerations in the analysis of group tasks.," *Psychological Bulletin*, vol. 55, no. 2, pp. 88–101, 1958.

[88] RTCA Inc., *Operational Services and Environmental Definition (OSED) for Unmanned Aircraft Systems (UAS)*. RTCA, Incorporated, 2010.

[89] RTCA Special Committee 228, "DO-365A Minimum Operational Performance Standards (MOPS) for Detect and Avoid (DAA) Systems," tech. rep., RTCA, Incorporated, Washington, DC, 2020.

[90] T. L. Seamster and R. E. Redding, *Applied Cognitive Task Analysis in Aviation*. Routledge, 2017.

[91] J. Cerreta, T. Bruner, and P. Snyder, "A10-Human Factors Considerations of UAS Procedures and Control Stations: Tasks PC-1 through PC-3, Pilot and Crew (PC) subtask, Recommended Requirements and Operational Procedures," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), August 2017.

[92] D. E. Kancler and D. A. Malek, "Using SMEs during initial development of small UAS concept of operations," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 2339–2343, SAGE Publications Sage CA: Los Angeles, CA, 2012.

[93] P. Venero, A. Rowe, and J. Boyer, "Using augmented reality to help maintain persistent stare of a moving target in an urban environment," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 56, pp. 2575–2579, SAGE Publications Sage CA: Los Angeles, CA, 2012.

[94] "Remote Identification of Unmanned Aircraft, RIN 2120-AL31, Federal Register, Vol. 86, No. 10," January 2021. https://www.govinfo.gov/content/pkg/FR-2021-01-15/pdf/2020-28948.pdf.

[95] "Operation of Small Unmanned Aircraft Systems Over People, RIN 2120-AK85, Federal Register, Vol. 86, No. 10," January 2021. https://www.govinfo.gov/content/pkg/FR-2021-01-15/pdf/2020-28947.pdf.

[96] M. L. Cummings, J. P. How, A. Whitten, and O. Toupet, "The impact of human-automation collaboration in decentralized multiple unmanned vehicle control," *Proceedings of the IEEE*, vol. 100, no. 3, pp. 660–671, 2012.

[97] A. Kopeikin, A. Clare, O. Toupet, J. How, and M. Cummings, "Flight testing a heterogeneous multi-UAV system with human supervision," in *AIAA Guidance, Navigation, and Control Conference*, pp. 1–18, 2012.

[98] P. T. Hu, B. Nelson, B. L. Nesmith, G. F. Thomas, and K. W. Williams, "Annotated Bibliography (1997-2019): Crew and Staffing Requirements of Unmanned Aircraft Systems in Air Carrier Operations ," tech. rep., Cherokee Nation 3-S and Federal Aviation Administration, n.d.

[99] E. T. Chancey, J. P. Bliss, Y. Yamani, and H. A. Handley, "Trust and the compliance-reliance paradigm: The effects of risk, error bias, and reliability on trust and dependence," *Human Factors*, vol. 59, no. 3, pp. 333–345, 2017.

[100] S. R. Dixon and C. D. Wickens, "Automation reliability in unmanned aerial vehicle control: A reliance-compliance model of automation dependence in high workload," *Human Factors*, vol. 48, no. 3, pp. 474–486, 2006.

[101] R. S. Gutzwiller, E. K. Chiou, S. D. Craig, C. M. Lewis, G. J. Lematta, and C.-P. Hsiung, "Positive bias in the 'Trust in Automated Systems Survey'? An examination of the Jian et al. (2000) scale," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 63, pp. 217–221, 2019.

[102] D. W. Lee, E. J. Bass, and C. Pankok Jr., "Developing operator-in-the-loop timeline requirements with a case study involving non-cooperative encounters with unmanned aircraft," in *2020 IEEE International Conference on Human-Machine Systems (ICHMS)*, pp. 1–6, 2020.

[103] J. D. Lee and N. Moray, "Trust, control strategies and allocation of function in human-machine systems," *Ergonomics*, vol. 35, no. 10, pp. 1243–1270, 1992.

[104] J. D. Lee and K. A. See, "Trust in automation: Designing for appropriate reliance," *Human Factors*, vol. 46, no. 1, pp. 50–80, 2004.

[105] R. C. Mayer, J. H. Davis, and F. D. Schoorman, "An integrative model of organizational trust," *Academy of Management Review*, vol. 20, no. 3, pp. 709–734, 1995.

[106] J. Meyer, "Effects of warning validity and proximity on responses to warnings," *Human Factors*, vol. 43, no. 4, pp. 563–572, 2001.

[107] L. Onnasch, "Crossing the boundaries of automation-function allocation and reliability," *International Journal of Human-Computer Studies*, vol. 76, pp. 12–21, 2015.

[108] R. Parasuraman and V. Riley, "Humans and automation: Use, misuse, disuse, abuse," *Human Factors*, vol. 39, no. 2, pp. 230–253, 1997.

[109] A. R. Pritchett, S. Y. Kim, and K. M. Feigh, "Measuring human-automation function allocation," *Journal of Cognitive Engineering and Decision Making*, vol. 8, no. 1, pp. 52–77, 2014.

[110] A. Steinfeld, T. Fong, D. Kaber, M. Lewis, J. Scholtz, A. Schultz, and M. Goodrich, "Common metrics for human-robot interaction," in *Proceedings of the 1st ACM SIGCHI/SIGART Conference on Human-robot Interaction*, pp. 33–40, 2006.

[111] E. J. Bass, L. A. Baumgart, and K. K. Shepley, "The effect of information analysis automation display content on human judgment performance in noisy environments," *Journal of Cognitive Engineering and Decision Making*, vol. 7, no. 1, pp. 49–65, 2013.

[112] J. M. Bradshaw, P. J. Feltovich, H. Jung, S. Kulkarni, W. Taysom, and A. Uszok, "Dimensions of adjustable autonomy and mixed-initiative interaction, AUTONOMY 2003. lecture notes in computer science," in *International Workshop on Computational Autonomy*, vol. 2969, Springer, 2003.

[113] J. Y. C. Chen, E. C. Haas, and M. J. Barnes, "Human performance issues and user interface design for teleoperated robots," *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, vol. 37, no. 6, pp. 1231–1245, 2007.

[114] J. Y. C. Chen and M. J. Barnes, "Human-agent teaming for multirobot control: A review of human factors issues," *IEEE Transactions on Human-Machine Systems*, vol. 44, no. 1, pp. 13–29, 2014.

[115] E. Edwards, "Automation in civil transport aircraft," *Applied Ergonomics*, vol. 8, no. 4, pp. 194–198, 1977.

[116] T. Fong and C. Thorpe, "Vehicle teleoperation interfaces," *Autonomous Robots*, vol. 11, no. 1, pp. 9–18, 2001.

[117] T. Fong, *Collaborative control: A robot-centric model for vehicle teleoperation*. PhD thesis, Carnegie Mellon University, 2001.

[118] E. Hollnagel and A. Bye, "Principles for modelling function allocation," *International Journal of Human-Computer Studies*, vol. 52, no. 2, pp. 253–265, 2000.

[119] D. W. Lee and E. J. Bass, "Simulating task sharing with delegation for autonomy and authority in air traffic control," in *2015 IEEE International Conference on Systems, Man, and Cybernetics*, pp. 962–968, 2015.

[120] S. Loft, P. Sanderson, A. Neal, and M. Mooij, "Modeling and predicting mental workload in en route air traffic control: Critical review and broader implications," *Human Factors*, vol. 49, no. 3, pp. 376–399, 2007.

[121] P. Maes, "Agents that reduce work and information overload," *Communications of the ACM*, vol. 37, no. 7, pp. 30–40, 1994.

[122] C. A. Miller and V. Rlley, "Achieving the associate relationship; lessons learned from 10 years of research and design," in *Proceedings of the 3rd International Workshop on Human-Computer Teamwork*, pp. 174–180, 1995.

[123] V. Riley, *Automation and Human Performance: Theory and Applications*, ch. 3. Operator reliance on automation: Theory and data, pp. 19–35. Lawrence Erlbaum Associates, Inc., 1996.

[124] W. B. Rouse, "Adaptive aiding for human & computer control," *Human Factors*, vol. 30, no. 4, pp. 431–443, 1988.

[125] N. B. Sarter and D. D. Woods, "Pilot interaction with cockpit automation: Operational experiences with the flight management system," *The International Journal of Aviation Psychology*, vol. 2, no. 4, pp. 303–321, 1992.

[126] N. B. Sarter and D. D. Woods, "How in the world did we ever get into that mode? mode error and awareness in supervisory control," *Human Factors*, vol. 37, no. 1, pp. 5–19, 1995.

[127] T. B. Sheridan, *Telerobotics, Automation, and Human Supervisory Control*. The MIT Press, 1992.

[128] P. N. Squire and R. Parasuraman, "Effects of automation and task load on task switching during human supervision of multiple semi-autonomous robots in a dynamic environment," *Ergonomics*, vol. 53, no. 8, pp. 951–961, 2010.

[129] M. F. S. John and M. A. King, "The four-second supervisor: Multi-tasking supervision and its support," *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 54, no. 4, pp. 468–472, 2010.

[130] C. D. Wickens, S. R. Dixon, and N. Johnson, "Imperfect diagnostic automation: An experimental examination of priorities and threshold setting," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, pp. 210–214, 2006.

[131] E. L. Wiener, "Cockpit automation," in *Human Factors in Aviation*, pp. 433–461, Elsevier, 1988.

[132] M. A. Goodrich and A. C. Schultz, "Human-robot interaction: A survey," *Foundations and Trends in Human-computer Interaction*, vol. 1, no. 3, pp. 203–275, 2007.

[133] M. Lewis, H. Wang, S. Y. Chien, P. Velagapudi, P. Scerri, and K. Sycara, "Choosing autonomy modes for multirobot search," *Human Factors*, vol. 52, no. 2, pp. 225–233, 2010.

[134] R. Oppermann, *Adaptive user support: ergonomic design of manually and automatically adaptable software.* CRC Press, 1994.

[135] C. A. Miller, H. Funk, R. Goldman, J. Meisner, and P. Wu, "Implications of adaptive vs. adaptable UIs on decision making: Why "automated adaptiveness" is not always the right answer," in *Proceedings of the 1st International Conference on Augmented Cognition*, pp. 22–27, 2005.

[136] C. A. Miller and R. Parasuraman, "Designing for flexible interaction between humans and automation: Delegation interfaces for supervisory control," *Human Factors*, vol. 49, no. 1, pp. 57–75, 2007.

[137] R. Parasuraman, S. Galster, P. Squire, H. Furukawa, and C. Miller, "A flexible delegation-type interface enhances system performance in human supervision of multiple robots: Empirical studies with RoboFlag," *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, vol. 35, no. 4, pp. 481–493, 2005.

[138] C. Pankok, Jr., E. J. Bass, P. J. Smith, J. Bridewell, I. Dolgov, J. Walker, E. Anderson, R. Concannon, P. Cline, and A. Spencer, "A7 - UAS Human Factors Control Station Design Standards (Plus Function Allocation, Training, and Visual Observer)," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), December 2017.

[139] C. Pankok, Jr., E. J. Bass, P. J. Smith, R. Storm, J. Walker, A. Shepherd, and A. Spencer, "A10 - Human Factors Considerations of Unmanned Aircraft System Procedures and Control Stations: Tasks CS-1 through CS-5," tech. rep., Alliance for System Safety of UAS through Research Excellence (ASSURE), August 2017.

[140] F. Friedman-Berg, J. Rein, and N. Racine, "Minimum visual information requirements for detect and avoid in unmanned aircraft systems," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 54–58, SAGE Publications, 2014.

[141] R. C. Rorie and L. Fern, "The impact of integrated maneuver guidance information on UAS pilots performing the detect and avoid task," in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 55–59, SAGE Publications, 2015.

[142] R. C. Rorie, L. Fern, and R. J. Shively, "The impact of suggestive maneuver guidance on UAS pilots performing the detect and avoid function," *AIAA Infotech@ Aerospace*, p. 1002, 2016.

[143] K.-P. L. Vu, R. C. Rorie, L. Fern, and R. J. Shively, "Human factors contributions to the development of standards for displays of unmanned aircraft systems in support of detect-and-avoid," *Human factors*, vol. 62, no. 4, pp. 505–515, 2020.

[144] J. Y. C. Chen, S. G. Lakhmani, K. Stowers, A. R. Selkowitz, J. L. Wright, and M. Barnes, "Situation awareness-based agent transparency and human-autonomy teaming effectiveness," *Theoretical Issues in Ergonomics Science*, vol. 19, no. 3, pp. 259–282, 2018.

[145] J. Chen, K. Procci, M. Boyce, J. Wright, A. Garcia, and M. Barnes, "Situation awareness-based agent transparency, ARL-TR-6905," tech. rep., Aberdeen Proving Ground (MD), US Army Research Laboratory, April 2014.

[146] J. Y. C. Chen, M. J. Barnes, A. R. Selkowitz, and K. Stowers, “Effects of agent transparency on human-autonomy teaming effectiveness,” in *2016 IEEE International Conference on Systems, Man, and Cybernetics (SMC)*, pp. 1838–1843, 2016.

[147] T. Helldin, U. Ohlander, G. Falkman, and M. Riveiro, “Transparency of automated combat classification,” in *International Conference on Engineering Psychology and Cognitive Ergonomics*, pp. 22–33, Springer, 2014.

[148] M. H. Draper, J. S. Pack, S. J. Darrah, S. N. Moulton, and G. L. Calhoun, “Human-machine interface development for common airborne sense and avoid program,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 58, pp. 44–48, SAGE Publications, 2014.

[149] L. Fern, R. C. Rorie, J. S. Pack, R. J. Shively, and M. H. Draper, “An evaluation of detect and avoid (DAA) displays for unmanned aircraft systems: The effect of information level and display location on pilot performance,” in *Proceedings of 15th AIAA Aviation Technology, Integration, and Operations Conference*, 2015.

[150] K. Monk, R. J. Shively, L. Fern, and R. C. Rorie, “Effects of display location and information level on UAS pilot assessments of a detect and avoid system,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 50–54, SAGE Publications, 2015.

[151] J. S. Pack, M. H. Draper, S. J. Darrah, M. P. Squire, and A. Cooks, “Exploring performance differences between UAS sense-and-avoid displays,” in *Proceedings of the Human Factors and Ergonomics Society Annual Meeting*, vol. 59, pp. 45–49, SAGE Publications, 2015.

[152] C. Santiago and E. Mueller, “Pilot evaluation of a UAS detect-and-avoid system’s effectiveness in remaining well clear,” in *Eleventh UAS/Europe Air Traffic Management Research and Development Seminar (ATM2015)*, 2015.

[153] D. J. Simons, “Current approaches to change blindness,” *Visual Cognition*, vol. 7, no. 1-3, pp. 1–15, 2000.

[154] C. M. Humphrey and J. A. Adams, “Human roles for robot augmented first response,” in *Proceedings of the IEEE International Symposium on Safety, Security and Rescue Robotics*, 2015.