Attentional Considerations in Advanced Air Mobility Operations: Control, Manage, or Assist?

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The implementation of automation will enable Advanced Air Mobility (AAM), which could alter the human's responsibilities from those of an active controller to a passive monitor of vehicles. Mature AAM operations will likely rely on both experienced and novice operators to supervise multiple aircraft. As AAM constitutes a complex and increasingly autonomous system, the human operator's set of responsibilities will transition from those of a controller, to a manager, and eventually to an assistant to highly automated systems. The development of AAM will require system designers to characterize these three sets of human responsibilities. The present work proposes different human responsibilities across various roles (i.e., pilot in command, system operator, system assistant) in the context of AAM along with pertinent attention-related constructs that could contribute to each of the three identified roles of AAM operators including situation awareness, workload, complacency, and vigilance.

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The emerging concept of Advanced Air Mobility (AAM) envisions safe, reliable, and accessible aerial transportation of passengers and goods within and between rural and urban areas (National Academies of Sciences, Engineering, and Medicine, 2020). Moreover, AAM will rely upon increasingly autonomous aircraft that will require automated systems to perform multiple tasks, altering the human's role (Chancey, et al., 2021; Pritchett et al., 2018). The successful maturation of AAM will likely require detailed characterization of human interactions with air vehicles leveraging various levels of automation (LOA), where lower levels indicate more human involvement and higher levels indicate more automation involvement in task completion (see Parasuraman et al., 2000 for description of LOA). Parasuraman et al. (2000), suggested that automation is often designed to support human information-processing stages at LOAs required by a task environment to sustain adequate performance levels for a given function. Mature Urban Air Mobility (UAM) operations (i.e., air taxies), a subset of AAM, envisage many aircraft operating over a single metropolitan area (Goodrich & Theodore, 2021), which may deplete the attentional resources of a human operator responsible for multiple vehicles (see Wickens & McCarley, 2008 for a review of attention research). To alleviate this, automation likely will be leveraged to support human sensory processing and perception/working memory stages by assuming information acquisition and analysis functions, respectively (Parasuraman et al., 2000). When the task requires operators supervise many vehicles, in addition to simplifying piloted operations, higher levels of automation could further support human decision making and response selection by assuming decision selection and action implementation functions, respectively (Parasuraman et al., 2000). However, how do span of influence, vehicle LOA, and task demand interact to impact operator performance? The present work proposes three sets of responsibilities that could emerge as a result of increasing LOA to support the expanding number of vehicles operating in AAM ecosystems: controller, manager, and assistant (cf. Mutzenich et al., 2021). Furthermore, we identify psychological constructs that are related to human attention systems for the identified roles.

Overview of AAM

The concept of AAM emerged in response to emerging needs to efficiently transport goods and people in fast-evolving markets of logistics and aviation. The technological advancement of electric propulsion, computer systems, sensors, and advanced automation collectively established the foundation for realizing the AAM concept. This emerging AAM environment involves the operation of either crewed or uncrewed air vehicles with varying sizes and missions. The subsets of AAM include, but are not limited to, UAM (National Academies of Sciences, Engineering, and Medicine, 2020) and a complimentary subset sometimes referred to as regional air mobility (Antcliff et al., 2021). Indeed, UAM will likely transition human influence over vehicles from direct control (e.g., simplified vehicle operations and/or remotely piloted aircraft), to management (e.g., remote supervisory operations), and then to a human offering assistance as needed (see Goodrich & Theodore, 2021 for description of UAM Maturity Levels). This transition presents critical human factors-related problems that can be posed in the following research question: How can we ensure successful human-automation interactions as fewer humans are tasked with controlling, managing, and assisting more vehicles?

Levels of Automation and Locus of Responsibility

In many domains, automation has played a critical role in mitigating, and unexpectedly, contributing to human error and workload (Lee & Seppelt, 2012). Automation is typically defined as a technology that replaces, to a varying degree, a function that was previously performed by a human operator (Parasuraman et al., 2000). In the AAM domain, aerial transportation will likely be supported by increasingly autonomous systems, which exceed the capabilities of traditionally defined automation (Chancey et al., 2021; Holbrook et al., 2020).

A myriad of studies on human-automation interaction report that the implementation of automation will alter human responsibility in ways that system designers cannot always anticipate (Billings, 1997; Parasuraman, 2000; Sarter & Amalberti, 2000). Indeed, humans in the AAM ecosystem will likely assume different responsibilities depending on the degree of automation authority. That is, automation can take over control of a human's responsibilities depending on the LOA (Parasuraman et al., 2000). Importantly, the change in LOA accommodates the changes in the locus of responsibility between the human and the automation (Sheridan, 2011). Several frameworks have conceptualized the relationship between the LOA and the locus of responsibility (Endsley, 1987; Parasuraman et al., 2000; Sheridan & Verplank, 1978). For example, Sheridan and Verplank (1978) suggested that humans can directly intervene in the automated system's task at lower LOAs, whereas automated systems allow less human intervention at higher LOAs. Furthermore, the LOA and locus of responsibility will likely vary across UAM Maturity Level (Goodrich & Theodore, 2021). Therefore, the human responsibilities (i.e., control, manage, assist) vary at different LOAs (however, see Roth et al., 2019 for alternative approaches to LOA).

METHOD OF HUMAN INFLUENCE

Various occupational domains have described human responsibilities differently (e.g., Endsley, 2017; Kaber & Endsley, 2004; Metzger & Parasuraman, 2001; van de Merwe et al., 2012), presumably due to different capabilities of the automated systems in each domain. In AAM, human responsibilities will likely vary as a function of the LOA required to accommodate increasingly complex, dense, and high tempo airspaces. The following sections will describe each category of human responsibility and identify relevant psychological constructs that may influence human-automation performance in AAM operations (see Table 1 for summary). Note that this list of psychological constructs is not meant to be exhaustive, and the constructs are perhaps not mutually exclusive to each human responsibility depending on specific task demands and requirements.

Table 1. Summary of role, associated responsibilities, and estimated span of influence for each human responsibility in AAM.

Responsibility	***Role***	***Span of Influence***
Control	Pilot in Command	1 human: 1 vehicle
Manage	System Operator	1 human: 10+ vehicles
Assist	System Assistant	Vehicles are highly automated, and direct human influence is significantly diminished due to cognitive limitations

Control

Similar to current operations, <u>a human pilot *controls* an aircraft if the human provides direct intent or goal setting for the aircraft and possesses the ability to execute the intent or goal by actively making changes on control surfaces.</u> Pilots will be tasked to control an aerial vehicle when operations involve relatively lower LOA (in comparison to manage or assist), and the locus of responsibility is with the pilot. A pilot is responsible for controlling a single aerial vehicle with basic and advanced automation capabilities, to include control mediated by fly-by-wire and flight management systems. Thus, an active controller's span of influence is 1:1, meaning that a single pilot can only operate a single vehicle.

Manage

In air traffic control, Metzger and Parasuraman (1999; 2001; 2005) characterized the term "manage" to describe the navigation of multiple aircraft flight paths. Specifically, the air traffic controllers assign pilots' flight paths to prevent collisions. Similarly, in the context of AAM, operators may be tasked to *manage* aircraft when the LOA increases, and human involvement reciprocally decreases due to the increasing capabilities of the automation. That is, operators will assign a flight path to highly automated aircraft, but they will not directly control the aircraft. Therefore, <u>a human operator *manages* aircraft if the operator actively sets a goal or intention of the aircraft but does not have the ability to directly control the aircraft.</u> Based on previous work investigating human performance with managing multiple vehicles, we anticipate that a single operator could manage approximately 10-15 vehicles (Cummings et al., 2014; Galster et al., 2001). However, we note that this number is an estimate based on existing tasks that approximate envisioned AAM operations.

Assist

As levels of automation increase, researchers suggest that the human's role may shift to a passive monitor that supervises highly automated systems (Bainbridge, 1983; Dekker & Woods, 2002). Furthermore, passive monitors are tasked to intervene in the automation's task when it fails (Bainbridge, 1983). Indeed, at the highest level of maturity of AAM, humans will not likely be directly controlling or even managing the aircraft. Instead, human influence may be limited to providing the goals for essentially autonomous aircraft (e.g., "fill these 20 deliveries"; see Hancock, 2017 for discussion on 'autonomous' systems). The automation will develop tactical plans (e.g., travel at 50 mph) and directly control the aircraft to achieve human-set goals. While the automation controls the aircraft, a human will supervise the automation and assist during system failure. Therefore, <u>a human *assists* multiple aircraft without active control or management, with an expectation that they intervene in off-nominal scenarios such as critical system failure or passenger emergency.</u> Importantly, the locus of responsibility for executing safe and reliable operations is with the automation and not a human.

PERTINENT PSYCHOLOGICAL CONSTRUCTS

Situation Awareness

Situation awareness (SA) is defined as the ability to perceive objects in an immediate environment (Level 1 SA), understand the meaning and arrangement of the objects (Level

2 SA), and project the future state of the environment (Level 3 SA; Endsley, 1995). In the context of aviation, failure to maintain SA can result in the pilot failing to detect system errors, despite being supported by the automation, known as the out-of-the-loop problem (Endsley & Kiris, 1995). The out-of-the-loop problem will less likely occur when a pilot in command is required to control a single aircraft. Furthermore, the out-of-the-loop problem may be avoided by implementing an aiding system that supports the operator's decision making. For example, Endsley (1997) asked participants to control a flight simulator to examine the effect of a SA-aiding system on the pilot's performance (measured as root mean squared error and time spent during pop-up threats). Results indicated that presenting displays that aid SA improved pilots' flight performance.

When managing multiple aerial vehicles, the detrimental effect of inadequate SA on performance could become more prominent. Endsley and Kaber (1999) examined each level of SA at various LOAs by employing a dynamic control task that required participants and/or automation to develop a strategy and eliminate target items. Results indicated that level 2 SA increased at intermediate-to-upper LOAs (i.e., humans and automation jointly make decisions). Furthermore, level 3 SA decreased at low LOAs in which decisions were generated solely by the human. Translating these results to AAM operations, operators managing multiple vehicles could possibly possess an adequate understanding of the aircraft's behaviors but make poor predictions of the aircraft's trajectory. In later work, Kaber and Endsley (2004) examined each level of SA at various LOAs using adaptive automation (i.e., automation allocation cycle time). Results indicated high level 2 SA at an intermediate LOA (i.e., involved human decision making) when the task was automated at low and medium time intervals.

Endsley and Kaber's (1999) work also suggests that system operators could present high level 2 SA and low level 3 SA at the highest level of automation, where the human is tasked to monitor the automation. Also, Kaber and Endsley (2004) demonstrated that level 2 SA was high even when the control task was fully automated and when the automation allocation cycle time was high. Generalizing these findings to AAM operations, if humans are tasked to passively monitor many aircraft, implementing adaptive automation may allow operators to maintain adequate SA. Additional research will be required to examine if the results from these studies translate well to environments envisioned in complex AAM-like operations.

Mental Workload

Mental workload is another important construct that will likely influence human performance in AAM operations. Workload is a hypothetical construct that represents the cost incurred by a human operator to accomplish mission requirements (Hart, 2006). Workload has been extensively studied in flight simulation environments aided by automated systems (Hancock et al., 1995; Hancock & Scallen, 1997; Karpinsky et al., 2018; Sato et al, 2020; Tiwari et al., 2009). Harris et al. (1995) measured the effect of automation on workload and performance in a multitasking environment involving the tracking, resource management, and multiple monitoring subtasks of the Multi-Attribute Task Battery (Comstock & Arnegard, 1992). When automation was engaged for the tracking task, participants reported lower levels of subjective workload and executed slower but more accurate monitoring and resource management performance. These results indicate participants effectively reallocated resources from the automated task to the manual tasks. Importantly, in a second experiment, Harris et al. showed that when participants were given volitional control to toggle automated control, their multitasking performance was better than under the fixed automation control condition. Translating these results to possible implications for AAM operations, a pilot could experience increased workload with a low LOA due to cognitive resource limits in the multitasking environment. Yet discretionary control of automated systems may offer the flexibility to effectively and dynamically allocate their cognitive resources to relevant tasks during operations.

Workload can also greatly influence an operator's ability to manage multiple vehicles (e.g., Cummings et al., 2014; Galster et al., 2001). Endsley and Kaber (1999) examined workload in conjunction with the impact of LOA on workload and performance recovery following automation failure in a dynamic control task. Analyses indicated that participants rated lower workload when the dynamic control task involved high LOA. Also, task performance increased as a function of increased LOA when automation operated normally. However, when the LOA was lowered due to automation failure, performance recovery was slower when the control task involved intermediate-to-high LOA than low LOA. An operator's workload could decrease as a function of increasing LOA. However, a potential caveat for increasing LOA is that the ability to recover from automation failure can degrade.

When AAM operations involve managing multiple air vehicles, performance could be affected by the amount of workload imposed by the task. Some studies have measured workload when monitoring multiple unmanned vehicles. For example, Parasuraman et al. (2009) compared workload between manual performance, performance involving static automation, and performance involving adaptive automation. They asked participants to manage multiple air and ground vehicles with the aid of automation while concurrently performing communication and change detection tasks. Results indicated that participants rated high workload when managing multiple unmanned vehicles without the automated aid. Furthermore, participants' workload declined when employing adaptive automation compared to when performing manually or with static automation. Based on these findings, managing multiple air vehicles could increase workload. However, adaptive or static automation could be employed to reduce the operator's workload (however see Kaber & Prinzel, 2006 for review of adaptive and adaptable automation research in aviation settings).

Complacency

The Aviation Safety Reporting System defines complacency as "self-satisfaction that may result in non-vigilance based on an unjustified assumption of satisfactory system state" (Billings et al., 1976, p. 23). Parasuraman and Manzey (2010) characterized complacency as an attitude that influences operators' monitoring strategies of system environments, further modulated by several factors including system properties such as LOA, reliability, consistency, and task context such as concurrent tasks and workload. Parasuraman et al. (1993) examined performance consequences of complacency at different variations of automation reliability in a low-fidelity flight simulation environment. Results demonstrated that keeping the reliability of the automation consistent and high induced complacency. Furthermore, the authors suggested that complacency can arise in multitasking environments. Indeed, human's functioning in an "assistant" role may be susceptible to complacency if tasked to passively monitor multiple highly automated aircraft. Also, complacency can be influenced by the temporal exposure of automation failure (i.e., first failure effect). Specifically, Roviera et al. (2007) reported that complacency increased, and in turn performance degraded, at the initial exposure of automation failure. During subsequent automation failures, complacency decreased and performance improved, perhaps due to the calibration of trust towards the automation. To this point, Parasuraman and Manzey (2010) suggested that complacency is associated with trust and attention allocation. That is, the visual sampling of the automated task is influenced by the human monitor's attention allocation strategy which is influenced by trust toward the automated system.

Vigilance

The mature AAM environment may require humans to monitor multiple highly automated aircraft over prolonged periods of time, inviting a classic issue of human performance, the *vigilance decrement*. Vigilance can be defined as the ability to sustain attention to an onset of a critical stimulus for an extended time (Warm et al., 2008). Research showed that operators' detection performance can drop over the course of 30 minutes or less (Mackworth, 1948), highlighting the temporally limited capacity of a human to function as a system monitor. Several models of sustained attention have been proposed. One popular perspective is the resource depletion model, which states that the task demands gradually exhaust attentional resources (Warm et al., 1996, 2008). Other models propose that attentional resources are drifted away from the task to task-unrelated thoughts due to failures of executive control of attention (Thomson et al., 2015) or mind-wandering (McVay & Kane, 2012). Modern automation technologies are designed to either replace or augment human functions and improve human-system performance, with the intention to alleviate human workload. Unfortunately, however, such technologies often shift human responsibility from an active controller to a passive monitor of even more complex technical systems, making their task more subject to vigilance decrement. Critically, if an AAM operational environment demands high working memory load, stimulus complexity, and sensory and cognitive processing, then vigilance decrements are more likely to occur.

CONCLUSION

The present work characterized different human responsibilities (i.e., *control, manage,* or *assist*) and explored attention-related factors that may support each role of a human operator as they relate to envisioned AAM operations. The high-level review conducted in this work indicates that human responsibilities vary depending on the LOA and the information processing load involved. For example, increasing the LOA may reduce human responsibility, transitioning the human's role from an active controller to a passive monitor. However, if the task requires the operator to manage multiple vehicles, then, depending on the LOA, the human responsibility may increase because of the net increase of task demand. Relying upon increasingly autonomous vehicles, a human may be tasked with supervising many aircraft in mature AAM operations. A plausible challenge with this paradigm is not whether automated systems to support such AAM operations can be developed, but whether human operators can adequately and safely execute such tasks given inherent limits of information processing.

The present work explored attention-related constructs that could influence human performance in envisioned AAM operations. These constructs included, but are not limited to, SA, workload, complacency, and vigilance. It is likely that human operators in future AAM operational environments will show similar performance characteristics due to these factors. However, rigorous and systematic experimentation in representative settings is necessary to obtain empirical data that more accurately represent human performance in envisioned AAM operations.

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