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The Underpinnings of Workload in Unmanned Vehicle Systems

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Acronyms and Definitions

DAA........................detect and avoid
fNIRS......................functinal near-infrared spectroscopy
FOV ....field-of-view
fps ....frames per seonc
GITZ ....Get-in-the-Zone camera
HAI ....human-automation intereaction
NASA ....National Aeronautics and Space Administration
PVACS ....Playbook-enhanced Variable Autonomy Control System
ROV........................remotely operated vehicles
UAC........................unmanned aerial vehicles
UGV........................unmanned ground vehicles
UUV........................unmanned underwater vehicles

The Underpinnings of Workload in Unmanned Vehicle Systems

Becky L. Hooey[1], David B. Kaber[2], Julie A. Adams[3],
Terrence Fong[1], and Brian F. Gore[1]

This paper identifies and characterizes factors that contribute to operator workload in unmanned vehicle systems. Our objective is to provide a basis for developing models of workload for use in design and operation of complex human-machine systems. In 1986, Hart [1] developed a foundational conceptual model of workload, which formed the basis for arguably the most widely used workload measurement technique—the NASA Task Load Index [2] [3]. Since that time, however, there have been many advances in models and factor identification as well as workload control measures. Additionally, there is a need to further inventory and describe factors that contribute to human workload in light of technological advances, including automation and autonomy. Thus, we propose a conceptual framework for the workload construct and present a taxonomy of factors that can contribute to operator workload. These factors, referred to as workload drivers, are associated with a variety of system elements including the environment, task, equipment and operator. In addition, we discuss how workload moderators, such as automation and interface design, can be manipulated in order to influence operator workload. We contend that workload drivers, workload moderators, and the interactions among drivers and moderators all need to be accounted for when building complex, human-machine systems.

1. Introduction

The introduction of advanced technologies in complex human-machine systems has led to a heightened need for evaluation of human performance impacts, automation reliability and operational risks [4]. Technological development and integration in system operations can change a human's role in relation to the system, e.g., transforming the human from a manual operator to a supervisor or a peer. In particular, as systems are increasingly automated, the human is often left in a passive monitoring role, a task that research has show that humans are ill-suited to perform [5]. Ironically, this role is not without operator workload or situation awareness demands, which can sometimes be greater than those associated with direct (manual) control [6]. Consequently, the modeling of workload in complex human-machine systems is a key element to supporting effective design and operations.

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The objective of this paper is to identify and characterize demand factors that contribute to operator workload in unmanned vehicle system operations. The work is intended to support an overarching goal of developing predictive models of workload for use in conceptual and detailed system design towards optimizing operator workload, performance and system/situation awareness. We begin by reviewing the conceptual model of workload developed by Hart [1]. We describe new and emerging mission-related factors that can impact workload and system design as well as discuss automation capabilities and interface features that can mitigate the influence of these factors.

1.1 Workload

Workload represents the task demand of accomplishing mission requirements for the human operator [3]. Hart and Staveland [2] proposed that there are three forms of task demands: Physical, Mental, and Temporal. Each form is multi-dimensional and may covary. While not discounting the importance of the other forms, in this paper we focus on *Mental (Cognitive) Workload*. Cognitive workload can be further delineated along three dimensions: Perceptual Load, Information Processing Load, and Response Load: Perceptual load refers to the effort required to perceive, detect, and identify objects in the world or environment; Information Processing Load refers to effort related to assessing and understanding the environment, weighing options, and making decisions; and Response Load refers to the effort required to select and execute a response [7].

Workload "emerges from the interaction among the requirements of a task, the circumstances under which the task is performed, and the skills, behaviors, and perceptions of an operator" [2]. In the framework developed by Hart, workload is *imposed* by a number of contextual factors including: operator objectives (goals and criteria), task temporal structure (duration, rate, and procedures), system resources available to execute the task (e.g., information, equipment, and personnel), and the environment. Hart [1] also included the notion of *incidental variables*, which may moderate imposed workload. Examples of incidental variables include system failures, operator errors, environmental changes, and operator state. In general, incident variables represent disturbances in otherwise nominal system operations.

Since Hart's seminal work, there have been many advances in our understanding of the workload construct as well as identification of additional demand factors that contribute to workload. With access to 30 years of empirical research that have followed Hart's paper, we are now in a position to inventory and describe the contextual variables that contribute to operator workload, as applicable to operators of unmanned systems, but with generalizability to operators of other complex systems.

Additionally, there have been significant advances in the state of technology, leading to increasingly automated and complex systems. Empirical research has documented that these increasingly automated systems have the potential to increase operator workload (e.g., adding new tasks associated with automation monitoring, management, and trouble-shooting automation failures or 'surprises'); change the nature of workload (e.g., shift the nature of workload from physical workload to cognitive workload); and create conditions of extended periods of perceived *underload* that has been shown to induce operator complacency [8].

Finally, there have been significant advances and a rich body of literature documenting the impact of advanced interface designs (synthetic and enhanced vision, multi-modal interfaces, etc.) and human-automation interaction methods (e.g., adaptive automation) on human operator workload.

Figure 1 presents our conceptual model of workload that identifies classes of drivers, which contribute to operator workload for modern human-machine systems, and specifically operators of unmanned vehicle systems. Within this conceptual framework, a taxonomy of ***Workload Drivers*** is proposed. ***Workload Drivers*** represent the myriad of contextual demand factors that directly contribute to the effort (i.e., perceptual, information processing, or response execution) required to complete a task in an allotted time frame. From a systems design perspective, these factors are considered constraints on the design process (i.e., they must be accounted for by a designer in defining the human operator's role). Workload Drivers are factors derived from the environment, task, equipment, and operator characteristics.

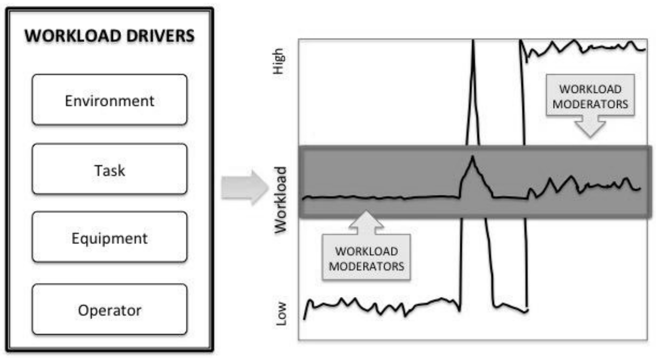

Figure 1. Model of workload drivers and moderators in contemporary complex systems operations.

Figure 1 also considers the finding that operators of highly automated systems demonstrate performance and behavioral effects of both high ("overload" [9]) and low ("underload" [10] workload as well as transitions between these states, which may lead to temporary workload bursts or spikes [11]. Extended underload has become a salient issue in complex systems operation with a major shift from direct (manual) control to supervisory control [12]. This issue has increasing relevance as systems evolve from automation to autonomy. While there may be general consensus that conditions of overload and underload exist [13], exactly how to objectively define the boundaries from optimal workload to overload or underload remains a challenge (e.g., [14]).

Ultimately, such boundaries need to be translated by designers into engineering controls (e.g., automation aids) or administrative controls (e.g., operator teaming) in complex systems in order to effectively manage operator workload by moderating peaks and valleys, as depicted in Figure 1. We define ***Workload Moderators*** as variables that the system designer can manipulate in order to optimize operator workload. Our analysis focuses only on the application of engineering controls to moderate workload. These moderators may include various types and levels of automation, or interface design (automation presentation) techniques. Although administrative controls, such as training, procedures, and human-human teaming can also moderate workload [15] [16] [17] [18] [19]; we do not addressed these in this paper.

Moderators can increase or decrease the magnitude of workload experienced by an operator and/or change the nature of workload. A workload moderator may eliminate the influence of a particular workload driver or shift operator effort from one form to another, such as from physical workload to cognitive workload.

Well-designed automation can moderate human operator workload to a level that is appropriate for effective performance of system tasks [4]. Of course, poor system design (e.g., not considering human factors guidelines leading to control incompatibility, display clutter, illegibility) can increase workload; however, this issue, while applicable to legacy designs, does not represent a pervasive negative workload moderator to be accounted for in modeling of original system designs.

A guiding framework to support automation designers was proposed [4] that identified four types of automation based on the human information processing task that is supported, including: Information Acquisition, Information Analysis, Decision Making, and Action Implementation. The authors [4] recommended that designers apply automation judiciously, or at the lowest level deemed necessary to realize desired performance and workload moderation benefits of automation. They noted that as automation is increasingly applied to decision-making functions, human operators are vulnerable to reduced situation awareness and complacency. In-line with this philosophy, we propose that to "optimize" operator workload, system designers must carefully identify the sources of workload and target automation at these sources. A systematic analysis is conducted in the remainder of this manuscript that considers workload drivers, identifies the information processing stages that are affected, and discusses the automation solutions that may mitigate those forms of workload.

1.2 Unmanned Vehicle Systems

The development of unmanned vehicle systems has transitioned from manual control to supervisory control or autonomous operations. Modern unmanned vehicle systems represent a wave of unprecedented automation and autonomy as well as sophisticated human-machine interfaces [20]. These systems present fundamental changes in how humans control and/or interact with complex machines [9] [21] [22] [23] [24] [25] [26] [27] [28]. As such, unmanned vehicle systems represent a useful domain for investigating how new forms of human-machine interaction impose new perceptual, information processing, and response demands on operators.

Many contemporary unmanned—or remotely operated—vehicles suffer from system design flaws that have contributed to accidents ([29] [30] [31] [32] [33] [34]) and are often exacerbated by inappropriate operator workload. While a common objective is single operator control of multiple unmanned vehicles, the present reality is that single vehicles typically require multiple operators (e.g., Predator). Inverting this relationship requires advances in system design, particularly from the perspective of operator workload management. An accounting of the factors that drive and mediate current unmanned vehicle operator workload can provide a basis to enable the transition to the desired state in which a single operator can control multiple vehicles.

The factors contributing to operator workload in unmanned vehicle systems are inherently contextually driven. Unique forms of human-automation interaction (HAI) influence individual operator workload when operating Unmanned Aerial Vehicles (UAV), Unmanned Ground Vehicles (UGV), and Unmanned Underwater Vehicles (UUV). The exploration of multiple domains of unmanned systems facilitates systematic identification and analysis of common factors that drive sub-optimal operator workload levels, including underload or overload. The contextual constraints on unmanned systems are considered as a basis for a "bottom-up" identification of the range of workload drivers and moderators across system types. In addition to identifying a common set of contextual workload drivers, this approach supports identification of the extent to which automation and interface design may be applied to moderate negative workload effects in UAV, UGV, and UUV operation.

Unmanned Aerial Vehicles (UAVs) range from small remotely controlled vehicles, which can be operated either within-line-of-sight or beyond-line-of-sight, to large highly automated vehicles (e.g., Global Hawk) that are capable of airborne operations for several hours or days. These systems are used for a wide range of purposes including recreation, commercial applications (e.g., photography, package delivery), first response, mapping, surveillance, and military.

Unmanned Ground Vehicles (UGVs) are used in a wide range of applications, including search and rescue, military combat, and planetary explorations. UGVs may be operated under manual control (teleoperation), either within-line-of-sight or beyond line of sight [29, 30]. While there are very few examples of fully autonomous UGVs, many ground vehicles are equipped with varying forms of automation, such as waypoint driving, terrain hazard detection and avoidance. NASA's Mars Exploration Rovers, for example, can perform autonomous driving between waypoints [35].

Unmanned Underwater Vehicles (UUV) include two classes of vehicles: remotely operated vehicles (ROVs) that may or may not be tethered (e.g., inspection of vessels, ports, deep water oil rigs); and "autonomous" vehicles (e.g., mine countermeasures, oceanographic research). ROV operators use a joystick to command thrusters to control vehicle position with multiple degrees-of-freedom, while countering tides, waves, and currents. The tether is connected to the host platform and provides a communication link to transmit command and data to an operator control station and the vehicle. Autonomous vehicles are typically pre-programmed to follow a series of waypoints, perform tasks (e.g., collect data) and return. These vehicles are untethered, and can travel long distances. Without the tether, communication bandwidth is usually unavailable, due to attenuation of radio waves and wireless signals through water [33].

2. Workload in Unmanned Systems

In Table 1, we identify a taxonomy of operator workload drivers that contribute to operator subjective perceptions of workload. It is comprised of four classes of demand factors including the environment, task, equipment, and operator. *Environment drivers* include degraded visibility, complexity, uncertainty, and environmental elements and stressors (e.g., noise, vibration). *Task drivers* include task demands, temporal demands, and task structure. *Equipment drivers* refer to the unmanned vehicle, its payload, and the communications link, which also includes properties of system components (i.e., the quality of cameras, sensors and the reliability of the link) as well as elements that influence vehicle stability and controllability. *Operator drivers* include task proficiency and individual differences (i.e., age, spatial ability).

Table 1. Taxonomy of Workload Drivers for Operators of Unmanned Systems

Workload Driver Class	*Sub-class*
Environment	• Degraded visibility. • Complexity. • Uncertainty. • Elements/stressors.
Task	• Task demands. • Temporal demands. • Task structure.
Equipment	• Vehicle. • Payload. • Link.
Operator	• Operator state and proficiency. • Individual differences.

Many of the identified workload drivers are akin to the variables identified in Hart's [1] original model. The unique aspect of the present inventory is the subclasses of drivers based on constraints of various unmanned system domains. The remainder of this paper provides a detailed assessment of each class and subclass of workload driver by considering the various unmanned system domains. Each driver is systematically evaluated to identify its potential to contribute to sustained underload, overload, or temporary workload spikes. Interface design solutions and automation solutions shown to moderate each workload driver are identified.

2.1 Environment Characteristics

When considering environmental factors in unmanned vehicle operations, we must account for both the vehicle's operating environment and the operator's control environment. Based on a review of literature, four subclasses of environmental factors were identified, including: degraded visibility, complexity, uncertainty, and environmental elements and stressors. The first three factors pertain to the vehicle situation, while the latter is most relevant to the operator's situation. Each is discussed in turn, with examples from the UAV, UGV, and UUV domains (see Table 2).

Table 2. Environmental Workload Drivers

Environmental Workload Sub-class	*UAV*	*UGV*	*UUV*
Visibility	• Fog. • Clouds. • Darkness. • Precipitation. • Particulates.	• Fog. • Darkness, dusk, shadows. • Brightness, glare, reflections. • Perceptual disturbances (e.g., opposition surge). • Dust/particulates (rain, hail). • Positive obstacles (buildings, boulders, vegetation). • Negative obstacles (holes, ditches, cliffs, canyons). • Graded/sloped terrain.	• Darkness. • Turbidity. • Structures (oil rigs). • Ice. • Sea life. • Underwater plumes/ vents.
Complexity	• Flight Environment (high vs low altitude; oceanic). • Traffic density (air traffic and ground environment). • Protected/restricted/special use airspace. • Combat zone, potential for communication/signal/ jamming.	• Surface environment: - Unconstrained, arid, barren, desert terrain; featureless snow field/dunes; lack of man-made terrain or landmarks. - Natural (trees, vegetation rocks, boulders) or man-made obstacles (buildings, bridges, vehicles). • Stability of surface composition. • Graded/sloped terrain. • Moving people/vehicles. • Combat zone, potential for communication/signal/ jamming. • Features limiting maneuverability/restricted access (e.g., stairs).	• Underwater environment: - Unconstrained, submerged. • Oceanic, open water: - Underwater mountains/canyons, buoys, sunken vessels, cables, shipping lanes. - Combat zone, potential for communication/ signal/jamming.
Uncertainty	• Dynamic traffic. • Weather (wind shifts, gusts, windshear, vortex) . • Unknown/unstructured/ unmapped (GPS restricted).	• Presence of other UGVs, vehicles, people, wildlife. • Shifting terrain, rockslides, quicksand. • Weather (wind gusts) . • Lighting (moving shadows). • Unknown/unstructured/ unmapped (GPS restricted).	• UUV in port/harbor/ shipping channels. • Surge, waves, tides, currents. • Unknown/unstructured/ unmapped (GPS restricted).

Table continued on next page

Table 2. Environmental Workload Drivers *(continued)*			
Environmental Workload Sub-class	*UAV*	*UGV*	*UUV*
Elements/ Stressors	• Absence of engine noise. • Absence of smell (smoke). • Absence of vibration. • Extreme temperatures, exposed to elements (wind, precipitation). • Lighting/glare, movement/ vibration. • Need for protective equipment (e.g., gloves). • Noise/distraction .	• Absence of proprioceptive and egocentric cues (extent of vehicle observation). • Absence of consistent clock time. • Extreme temperatures, exposed to elements, (wind, precipitation). • Lighting/glare, movement/ vibration. • Need for protective equipment (e.g., gloves). • Noise/distraction. • Microgravity.	• Absence of proprioceptive and exteroceptive cues. • Extreme temperatures, exposed to elements, (wind, precipitation). • Lighting/glare, movement/vibration. • Need for protective equipment (e.g. gloves). • Rough seas. • Noise/distraction.

2.1.1 Environmental Workload Driver: Degraded Visibility

Environmental factors that degrade visibility can increase operator workload in vehicle control and navigation tasks, either by limiting an operator's ability to see the vehicle in the remote environment (particularly for within-line-of-sight operations) or reducing the camera and sensor output quality used by the remote operator to navigate the vehicle. Examples applicable to all three domains (UAV, UGV, and UUV) are presented in Table 2. UAV operators contend with reduced visibility due to fog, clouds, the presence of particulates (i.e., rain, hail, dust) and reduced vision at night. UGV operators experience these same workload drivers, as well as demands due to glare, shadows, reflections, and other perceptual disturbances, such as opposition surge, (a brightening of a rough surface when the illumination source is directly behind the operator). Other environmental objects may obstruct or obscure visibility, including positive obstacles (i.e., buildings, vegetation) and negative obstacles (i.e., holes, ditches, canyons) and graded or sloped terrain. Likewise UUV operators experience limited visibility as they operate in dark and turbid waters and less frequently visibility may be obscured due to structures (such as oil rigs), ice, sea life, and underwater plumes and vents [33].

A key consequence of limited visibility is the increased difficulty of accurately estimating vehicle position, vehicle speed, and the presence and location of environmental hazards. Thus, the workload associated with maneuvering the vehicle, navigation, and avoiding obstacles and hazards may be significantly increased. The effect on workload may be a short-term spike, as is the case of a UAV flying through a cloud for example, or may be a longer duration increase, as is the case of human control of a ROV in an impoverished environment due to darkness and turbidity, or a UGV operating at night or in a highly constrained space, such as a collapsed building.

2.1.2 Moderating Workload: Degraded Visibility

Interface design solutions that replace or augment degraded or absent visual cues can moderate this form of workload by supporting information acquisition. Examples include enhanced and synthetic vision navigation displays (e.g., [36] [37]) or automated highlighting and cueing of environmental obstacles to support obstacle detection. In addition, interface features such as graphical overlays of distance and speed information on impoverished video-feeds can be used to reduce operator workload with limited visual cues. However, operator use of such features may induce new forms of workload by requiring foveal vision to read digital or analog readouts, rather than acquiring the same information from peripheral vision cues and optical flow. In the case of high-demand visual displays, additional modalities of information presentation, such as auditory and haptic cueing (e.g., [38]) can be used to further moderate workload and support navigation. Lastly, increasing levels of automation and/or autonomy may also directly reduce this form of workload by supporting action implementation.

2.1.3 Environmental Workload Driver: Complexity

The complexity of the environment in which the vehicle is operating is defined by the density and nature (i.e., static or dynamic) of hazards that must be avoided. Operators must develop and maintain an understanding of the spatio-temporal relationship of the vehicle relative to the environment, mission objectives, landmarks, and hazards in order to make decisions about when and how to deviate to avoid these hazards. For example, UAV operators experience higher workload when flying at low altitude, near protected or restricted airspace, combat zones or populated areas. UGV operator workload is heightened by the presence of natural obstacles, such as rocky terrain, vegetation, and man-made obstacles, such as buildings. UGV operator workload may also be increased in the presence of unstable surface composition, such as quicksand, or graded terrain. Research [39] showed that UGV operator workload varied as a function of terrain, with significantly higher workload occurring in the presence of difficult-to-navigate terrain features, such as ravines. UUV operators face increased workload due to natural obstacles (e.g., underwater mountains, canyons) and man-made obstacles (e.g., buoys, sunken vessels and cables). These forms of environmental complexity can result in either long-duration high workload, or temporary spikes in workload depending on the density of obstacles.

In contrast, environments that are barren and lack landmarks, can also contribute to operator workload, as the operator lacks references to support environmental awareness and navigation. Examples include UAV operators when flying at high altitude or over open-water oceanic environments, UGV operators when operating in barren desert terrain, and UUV operators when the UUV is submerged in open water.

2.1.4 Moderating Workload: Environmental Complexity

Addressing workload associated with environmental complexity is multi-faceted. There is a need to support operators in very complex environments that may be cluttered with many obstacles to be avoided. Interface technologies in support of information acquisition tasks may be used to reduce operator visual demands. Examples include display “declutter” algorithms [40] [41], and display-based highlighting and cueing of safe routes. To support information analysis, workload moderators may include automated target and object identification systems and autonomous terrain analysis [35]. While navigation aiding and automated re-routing may be employed to support decision selection, increasingly autonomous systems, may support action implementation. In visually complex environments, visual workload can be addressed by replacing visual cues with tactile or auditory cues [42] [43].

In contrast, mitigating workload in sparse low-complexity environments may require different tools such as navigation aids, automated positioning systems, and graphical overlays on video interfaces, such as position reference grids [44].

2.1.5 Environmental Workload Driver: Uncertainty

Environmental uncertainty contributes to workload associated with vehicle control, navigation and hazard avoidance maneuvers. Sources of environmental uncertainty may include dynamic atmospheric and meteorological conditions, such as unexpected shifts in winds (i.e., wind shear) and wave/currents (i.e., surge, rogue waves) that increase workload associated with vehicle control. The presence of moving vehicles, objects, or people that must be avoided also reduces environmental predictability and imposes workload due to the additional tasks of prediction and extrapolation (e.g., vehicle location at a future time relative to a moving vehicle or weather cell [45]). Proximity to traffic and the traffic type, (e.g., manned or unmanned, friend or foe), may interact with operator workload. The dynamics of a moving vehicle (i.e., slow or fast, constant or variable speed) also plays a role in determining operator workload.

2.1.6 Moderating Workload: Environmental Uncertainty

Auto-stabilizing technology may mitigate physical workload associated with the demands of controlling the vehicle in unpredictable environments such as instances of windsheer or turbulence for UAVs, or unpredictable currents for UUVs. Likewise, automation to enable the vehicle to automatically sense and avoid dynamic objects (traffic) may mitigate workload in environments that are heavily populated with other moving vehicles With less autonomy, Detect and Avoid (DAA) display technology can support operators to the extent that it has the capability to present position information (e.g., vehicle range, bearing, etc.), direction information (e.g., directionality, heading), predictive displays (e.g., yellow and red alert color-coding, 30 second dead-reckoning vector lines to intruders), and rate information (e.g., ground speed, history trails, climb/descent rates [46] [47]). Interfaces that support trajectory prediction and extrapolation over time, as well as estimates of closure rate, may also be useful for mitigating workload. Another workload moderator is dynamic geofencing, in which areas of severe weather, unstable winds, or congestion, can be indicated and automatically avoided by the unmanned vehicle [48] [49].

2.1.7 Environmental Workload Driver: Elements and Stressors

This class of workload driver pertains to the environment from which the operator controls the vehicle and may range from portable field stations to sophisticated dedicated control facilities for UAV operators [32]. UGV operations may be controlled from moving vehicles or control centers (e.g., dedicated or field deployed). UUV operations may be controlled from shore or on-board a waterborne vessel (e.g., ship or small watercraft). Operating in the field may subject the operator to environmental stressors, such as extreme lighting conditions (i.e., too dark, too bright), extreme temperatures that require personal protective gear, and sound/noise distractions. These stressors can increase operator workload due to discomfort or encumbrance. For example, controlling an UGV from a moving vehicle or an UUV from a rigid hulled inflatable boat, may increase operator workload due to the presence of vibrations or motion.

The *absence* of environmental elements is another known workload driver, which has been well documented with UAV operators [50] [32]. Often operators function in relative "sensory isolation" from the aircraft under their control due to a lack of ambient visual input, kinesthetic/vestibular information, and sound [50]. All of this sensory information is valuable for maintaining awareness of the environment and system conditions (e.g., turbulence). Such information can provide operators with cues to vehicle speed, bank angle, aircraft tilt, air, ground and sea elements in the vicinity, weather conditions, and engine health [51].

Clock time, in some situations, can also be an environmental stressor. For example, during the primary mission phase of the Mars Exploration Rovers, the ground control team worked on a "Mars time" schedule [52], i.e., staying synchronized with the Mars "sol" (approx. 24 hours and 40 minutes). This synchronization required operators to migrate their work shifts by 40 min each day, which led to numerous difficulties including fatigue and stress [53] [54].

2.1.8 Moderating Workload: Elements and Stressors

Moderating environmental effects and stressors present a multifaceted challenge. Exposure to environmental stressors, such as extreme temperature, sub-optimal lighting, noise, and vibration can be mitigated in various ways including automation and interface design. Each deployment environment must be examined individually to determine the best technique for moderating sources of workload. Sensors can be used to monitor and regulate operator environment thermal conditions as well as sensory cues. Environmental stressors can also be reduced via effective interface design. For example, vibration-induced workload can be mitigated by enlarging the size of display fonts and soft-keys, enhancing saliency of critical information, damping vibration effects at input devices, and replacing visual with auditory output [55].

Workload attributed to the absence of environmental elements can also be addressed by system design. Automated technologies can artificially generate sensory cues in the operator environment representative of vehicle operational behaviors, such as fly-by-wire haptic feedback and engine noise generators. Immersive visualization can provide a sense of telepresence [56]. Multi-modal information displays, such as combining visual, auditory, and tactile cues, can compensate for the missing natural tactile and auditory cues [36]. Graphical data overlays of vehicle distance and speed information, may also mitigate the loss of environment information. However, the nature of workload also changes in such situations. For example, a digital speed readout requires foveal visual attention as compared to assessing speed through peripheral vision using optical flow cues.

2.2 Task Characteristics

The aspects of the unmanned vehicle operator's task that contribute to workload may be divided into three categories: task demands, temporal demands, and task structure (see examples of each in Table 3).

2.2.1 Task Workload Driver: Task Demands

Task demands, including the criticality of the mission, severity of consequences, reversibility of decisions, and the required level of precision can contribute to an operator's workload. Examples of task demand factors that are relevant for each of the three unmanned systems subdomains are presented in Table 3. While these factors may be applicable across all subdomains, they may be defined differently for each group of operators and have different workload implications.

Table 3. Task Workload Drivers

Task Workload Sub-class	*Examples*
Task Demands	• Mission complexity. • Mission criticality. • Frequency, nature, and duration of interventions. • Level of performance required. • Consequence of task failure. • Reversibility of decisions . • Predictability of tasks. • Need for fault management, fault handling, fault recovery tasks. • Preparation and rehearsal of fault contingencies.
Temporal Demands	• Density of route waypoints, hazards, obstructions. • Task duration. • Operational tempo. • Time constraints/pressure. • Exogenous vs endogenous temporal control. • Rapidity of fault onset.
Task Structure	• Dual-task/multi-tasking requirements (e.g., one operator, multiple ROVs). • Task requires coordination / collaboration (e.g., many operators, one ROV). • Task interruption. • Hand-offs. • Procedures (many/complex, branching, looping, spawning new task, etc.). • Coordination and scheduling subtasks. • Dependencies with other systems, components, ill-defined tasks.

In an example of the effect of mission criticality, one study [57] demonstrated that perceived workload differed as a function of the type of military unit supported. Specifically, when supporting infantry units perceived workload was higher than when supporting other less vulnerable units not operating in dangerous combat zones.

The potential for loss-of-control of a vehicle can substantially contribute to workload, especially if the loss results in significant vehicle damage/destruction or threatens people and property [58] [32]. UAV pilots, during an emergency, may be required to destroy the aircraft by a controlled impact, ditching, or other flight termination method and the operator is responsible for protecting life and property on the ground [32]. The vehicle replacement cost in terms of time, effort, or financial expense may also contribute to perceptions of workload (e.g., increased effort to maintain vehicle integrity), particularly if the cost is high or the vehicle is irreplaceable. The decisions associated with when, where and, how to terminate a mission increase information processing and workload. Interacting with mission criticality and severity of consequences is the required degree of precision or level of task performance. It has been found that more deliberate missions (i.e., cautious approaches) resulted in higher operator workload [39].

Task demands can be defined by the frequency, duration, nature, and complexity of operator interventions—all of which can strongly influence workload. If the need to intervene is too infrequent, the operator may experience underload, whereas frequent intervention may lead to overload. When the need to intervene follows an extended period without interaction, a temporary workload spike may occur, while the operator regains the awareness needed to intervene effectively. The degree of operator absence from system control, due to automation, can influence the reorientation cost.

2.2.2 Moderating Workload: Task Demands

Generally, high task demands contribute to cognitive workload associated with decision-making tasks. As such, supporting operators in decision-making tasks via decision aids and other support tools may moderate workload. Action rehearsal or "what-if" decision support tools (e.g., [59]) may mitigate cognitive workload. Such tools allow the operator to simulate a vehicle maneuver and visualize the outcome, before commanding the actual system. When this capability is infeasible, or undesirable, enabling the operator to reverse or 'undo' decisions can also mitigate workload [60].

Interface designs that incorporate multi-modal redundancy may moderate workload for applications in which information transmission security is critical to avoid loss of control or other severe consequences. For example, a unique redundant alert for critical warnings, whether aural or tactile, was shown to help participants differentiate warning types and improve reaction time to critical events when performing multiple tasks with a simulated UAV control station [61]. Multi-modal interfaces, including touch screens, speech synthesis and location-based audio/haptic assistance, have been shown to improve operator performance and lower workload [62].

Operator underload, caused by an infrequent need to intervene, remains a task design issue. Strategies to moderate underload include structuring task assignments or function allocations based on near real-time assessments of operator workload or visual attention allocation to task displays. Instead of identifying opportunities for introducing decision aiding and support tools to off-load operators, underload requires effective means of automation task-shedding to human operators. Underload can also be addressed by invoking requirements for operator communication on task performance (e.g., verbal protocols).

2.2.3 Task Workload Driver: Temporal Demand

Temporal demand is defined by a number of mission features. Route complexity dictates event rate and can be defined in terms of the number and density of waypoints, heading changes, and altitude (air) or depth (under water) changes. As the density of events increases, so does workload, but at the same time, low density may lead to underload and operator boredom and vigilance decrements [63].

Another temporal driver is the *mission duration*, which can range from minutes to days, or even years (in the case of planetary rover missions). Mission duration can interact with vehicle control mode to impact workload. Under manual control, long duration missions can result in higher operator workload [57], and fatigue; whereas, under supervisory control an operator may be subject to extended periods of monitoring leading to vigilance issues and underload.

Operational tempo refers to the time available to make decisions or the rate at which decisions must be made. Research [64] has found that time pressure, created by high operational tempo in UAV control, generally degrades performance and increases workload. One factor that contributes to operational tempo is the vehicle's speed, and the resulting closure rate between the vehicle and other objects that must be avoided. UAVs move at high speeds relative to other classes of unmanned vehicles, and fixed wing UAVs cannot stop so that the operator can assess the environment or mission status, if the need arises. This operational condition can impact the speed at which operators must process information and react, which increases temporal workload as well as the perceptual and information processing demands.

Another temporal workload driver is the extent to which the pace is *endogenous* or *exogenous*. Endogenous events are dictated by the operator, such as the decision to replan a path to reach a goal in a shorter time period [65]. Exogenous events result from unexpected external environmental conditions, such as emergent threat areas that require replanning vehicle trajectories [65] and can contribute to perceived workload.

2.2.4 Moderating Workload: Temporal Demand

When temporal demands require decisions and actions in short time periods, supporting action implementation with highly automated systems that automatically respond to environmental threats (e.g., traffic avoidance automation) may effectively ameliorate workload. Tools that support temporal management, such as scheduling tools and timeline displays that provide historical and predictive views [66] [67] may moderate such sources of workload. It is also beneficial if task rescheduling activities are user-initiated.

2.2.5 Task Workload Driver: Task Structure

The manner in which tasks or missions are structured can impact workload [68] [69]. For example, workload can be impacted when coordination across co-located or distributed groups is required, and the degree to which the tasks are interrelated. Complex missions can require the operator to monitor and manage a large number of mission-specific aspects, which increases workload.

A prominent factor that determines task structure is the Operator to Vehicle ratio. Currently, typical missions involve multiple operators controlling a single unmanned vehicle. For example, UAV missions typically require a pilot and a sensor operator [70]; and may also include a mission commander, launch crew (1-3 people) and mission crew (2-5 people) [71]. However, commonly cited goals seek to enable a single operator to control multiple UAVs [34] or multiple operators to control multiple vehicles (e.g., [72] [73]). Recently, there has been interest in human-swarm interaction, which posits that a single operator can effectively manage the actions of a "collective" of hundreds (or thousands) of vehicles. However, it has been shown that an increase in the number of assets under operator control results in increases in workload [22] [74] [75] [76]. Based on unpredictability of workload variations in UAV operations, and degradations of operator performance, some researchers have suggested limiting control responsibilities to no more than two vehicles ([77] [78] [79]) and only one under emergency conditions [77]. Related to this, Cummings et al. [80] identified 70% operator utilization (percent busy time) as a threshold for significant performance decay in supervisory control of autonomous vehicles.

Enabling a single operator to control multiple vehicles requires a change in task structure, shifting from low-level tasks and manual flight control, to high-level mission management or increasingly automated or autonomous flight [73] [81]. Increasing the number of UAVs controlled by one operator can hinder operator performance in time-critical supervisory control tasks by increasing operator workload, thereby impacting the operator's attentional resources [82] available to service additional tasks.

Further, the task structure for a single operator to many vehicle ratio implies the need for operators to divide their attention across numerous tasks [83] as well as the need to quickly and accurately switch between tasks [84]. Task switching, or switching among information sources (i.e., tasks, missions, video feeds, or camera manipulations), can be cognitively demanding. The cognitive costs of switching may also include loss of situation awareness. When an operator switches between tasks (e.g., switching from navigating using a set of sensory input to data analysis using another set of sensory input; or switching attention from one vehicle to another), the mental effort required to regain awareness on each task increases the operator's cognitive resource demands and the time required to perform the necessary mental processes to make the context switch [36]. Workload, particularly mental and temporal demands, and mental stress were much higher for operators controlling three different types of robotic assets than operators controlling two different assets or a single asset [57].

Whether controlling a single vehicle or multiple vehicles, when teams of operators work together, additional workload occurs due to the interaction among operators as they collaborate to complete a mission. Workload is dictated by the amount and nature of coordination required among team members, the need for transfer of control/tasks between operators, and the amount and complexity of required procedures. Control handoffs may occur between co-located consoles or between physically separated control stations [31] at geographically distributed locations [85]. For example, control of a long endurance vehicle may be transferred multiple times during a single mission [86]. Handoffs require tightly coordinated interactions via system interfaces. Factors such as shift changes or operator distraction may breakdown coordination, resulting in an unsuccessful handoff and increased workload [85]. Handoffs represent one of the many workload drivers in human-machine and human-human task collaboration [15] [17] [18]. However, a thorough examination of factors that may include team member roles, team structure and organization, team member skill sets, and methods of communication is beyond the scope of the present review.

2.2.6 Moderating Workload: Task Structure

A number of methods have been proposed to address workload associated with task switching and task sharing, often experienced when operating more than one vehicle. One class of interface design technologies includes memory aids that present historical images or data [87]. One example is an interactive event timeline that visually summarizes past events [88] [89]. Another example is the *Interruption Assistance Interface*, which consists of a replay window, an event timeline, and a set of animation controls that display historical views for UAV supervision and replanning [89]. Automated summarization systems [90] can improve situation awareness when supervisory control is employed, or when the operator is only intermittently involved with vehicle operations.

Displays that support the rapid acquisition of spatial awareness may be applied to mitigate workload. For example, the *Airspace Transition Display* [91] provides airspace information (e.g., clearances, point of contact, instructions) at a glance that can be critical during operator handoffs. Similarly, the *Get-in-the-Zone camera (GITZ) transition display* allows operators to rapidly develop situation awareness and minimize negative transfer effects when switching between multiple UAV missions and their associated camera views [84]. GITZ uses visual momentum to support rapid comprehension of relevant information following the transition to a new display [92].

Multi-modal displays have helped avoid overloading the visual channel and moderate workload. Visual cues for system fault monitoring was shown to require more mental workload than tactile or combined tactile and visual cues [93]. The tactile cue resulted in faster response time and less interference with the concurrent tracking task. Tactile cueing for vehicle course deviations and arrival times aided in monitoring multiple UAVs [83]. Similar benefits for sonification of system alerts was found in terms of operator reaction time, but with no impact on workload [94].

Finally, narrative-based displays [95] have the potential to express dense information that is easier for operators to understand. In particular, story-based summaries driven by accumulated spatiotemporal information may be superior to simple playback (in real-time or faster) of logged telemetry data.

2.3 Equipment Characteristics

Several facets of unmanned vehicle equipment can also impact operator workload, including the vehicle's physical characteristics, the onboard payload (especially that used to perform tasks associated with vehicle control, navigation, and hazard detection and avoidance), as well as the characteristics of the command, control and communication link (see Table 4 for examples).

Table 4. Equipment Workload Drivers

Equipment Workload Sub-class	*Examples*
Vehicle	• Maneuverability. • Stability. • Size. • Number of actuators/degrees of freedom/ kinematics. • Power capacity and consumption. • Ruggedness, robustness, replaceability. • Monetary value.
Payload	• Availability and number of camera/sensors. • Payload complexity (amount and nature of manipulation required). • Quality of cameras/sensors—low resolution, slow update rate, noise. • Camera misalignment, propensity for visual illusions. • On-board perceptual processing capacity, and reliability. • Limited field-of-view. • Look-ahead (illumination, camera /sensors.
Link	• Communication/control latency/variability. • Low bandwidth. • Link unreliable—intermittent. • Link unavailable—corrupted, signal jammed, link off.

2.3.1 Equipment Workload Driver: Vehicle

Vehicle characteristics that affect maneuverability and stability, such as vehicle size, form factor, speed and kinematics can directly impact operator workload. The basic vehicle kinematics directly factor into the complexity of maneuvering a vehicle. Non-holonomic vehicles (e.g., skid-steered) place demands on the operator to map the vehicle motion to the actuator control sequence. Additionally, motion control performance limitations (i.e., slow actuators, maneuverability) can increase the difficulty of control and, thus, workload.

Ground vehicles, by their nature, tend to be more stable to maneuver. Smaller UAVs and UUVs are susceptible to environmental factors, such as wind or currents. Further, unmanned vehicles have varying means of maneuvering throughout environments. UAVs may be fixed-wing motorized, fixed-wing glider, or multi-rotor. UGVs may have wheels, treads, legs, etc. Depending on the specific type of UGV locomotion, environment characteristics, can hinder locomotion. For example, tracked vehicles tend to maneuver more reliably on stairs than wheeled vehicles.

All unmanned vehicle types are equipped with payloads that include sensors and actuators, such as manipulators, arms or hands. Typically, as the number of actuators increases, or complexity of the vehicle's kinematic control increases, the interaction demand to control the vehicle also increases. Traditional operator control units, such as those used for the Andros Mark 5 robot, require operator attention to video feedback from camera and use a joystick to manipulate the various actuators, which results in kinematic control modes that increase workload demand. Furthermore, such control units do not provide tactile feedback contributing further to the operator's visual channel load. Monitoring and managing a vehicle's power capacity and consumption are generally not significant workload drivers for UGVs (planetary rovers are a notable exception). However, operators of many UAVs and UUVs must closely monitor power consumption, due to limited power capacity; thus, adding to the workload burden. Further, the value, ruggedness, robustness and replaceability of the vehicle, or its components, can also drive workload.

2.3.2 Moderating Workload: Equipment/Vehicle

Vehicle capabilities to sense and communicate impending or current faults, such as diminished fuel levels or inability to move to a positional goal [96] can serve to mitigate workload for operators. Information displays that support operator understanding of the current state of a vehicle can moderate equipment-related workload. Fault detection displays can be developed for this purpose [97] [73]. Prior research [98] has found that displays presenting fault and equipment status information, combined with the use of multimodal feedback, including tactile and visual channels [61] can significantly reduce operator workload.

Further, as the degrees of freedom and the diversity of the actuators increase, it is recommended to unify the tasking, rather than separating the tasks into individual aspects, such as locomotion and manipulation [19]. With respect to interface technologies, immersive (virtual) environment have been shown to facilitate maneuvering of complex robots with very high degrees of freedom in complex tasks, such as Robonaut [99]. Such display technologies may allow operators to better manage high workload circumstances due to certain equipment designs.

2.3.3 Equipment Workload Driver: Payload

Operators routinely use camera and sensor payloads to determine pose and to detect geometric hazards when remotely operating a vehicle[4]. This task requires the operator to use imagery to search for objects and obstacles relevant to vehicle control, to estimate distance and orientation, etc. [29,30,100]. This task often necessitates that operators expend significant effort engaged in camera integration and management. The vehicle itself may be equipped with multiple cameras (e.g., first-person, tail, angled, belly, and overhead), which may be synchronized with video feeds from other sources (e.g., other vehicles, ground support, digital terrain maps). The task of controlling these camera views and integrating views from multiple feeds increases workload [101].

A study [102] was conducted to assess the effect of camera type (single, dual and projection) on operator target detection performance, self-assessed workload and an objective indicator of cognitive demand based on blood oxygenation levels using Functional Near-Infrared Spectroscopy (fNIRS). Results showed a significant increase in workload for the dual camera condition, with the fNIRS measure. Related to this latter finding, another study showed that image manipulation, mental rotation, and close image inspection tasks produced high cognitive demands [103].

Narrow field-of-view (FOV), low update rates, and poor resolution may also increase operator workload [104]. Across all unmanned vehicle domains, the reduced FOV inherent in video imagery (i.e., the "soda-straw effect" or "key hole effect" [105]) is a source of operator workload in that it eliminates ambient visual information needed for assessing ego-motion [106] [107], while also imposing a demand for greater camera scanning for successful hazard detection [50]. Onboard views (egocentric with limited FOV) were found to produce higher average cognitive workload than a chase camera view (exocentric) [102].

Low image update rates contribute to workload by degrading the perception of motion information [50]; whereas, poor spatial resolution can impair detection of objects that occupy only a small visual angle within an image. Reducing the frame rate to 2-4 frames per second (fps) negatively affected a teleoperator's performance in navigation duration (time-to-task completion) and increased perceived workload [104]. Extra effort was required to interpret low-quality video feeds which increases perceptual loads. Decreased resolution and increased scene distortion associated with scene compression may increase cognitive workload in vehicle control, navigation, and object localization tasks [104].

2.3.4 Moderating Workload: Equipment/Payload.

Payload management is a large contributor to workload. Consequently, many research efforts have aimed at optimizing unmanned vehicle system design and configurations in order to minimize this source of workload. For example, the Castling Rays payload-switching decision aid [84] enables operators to view, on a video stream, which payload has the best view of a target at any given time. Dynamic layout and automatic window resizing tools that present the most important or relevant payload feed [108] represent another approach. Use of this type of technology does require contextual information, such as operator task goal states. Further, a vehicle coupling capability can be used to allow one vehicle to follow another [84] and for multiple payload points-of-view to be coupled, which allows operators to share the same video quality and zoom settings.

[4] Unmanned vehicles often include other task-specific payloads, but those are beyond the scope of this paper.

Workload attributed to integrating information from multiple cameras or sensors may be moderated by fusing several sensor/camera feeds together into a single display. For example, multi-sensor displays [20] that combined information from several sensors or data sources to present a single integrated view improved situation awareness, depth judgment, and decision-making speed [109].

Managing workload attributed to restricted FOV is a challenge. One study [110] investigated two methods of providing an operator with additional contextual information: widening the FOV and capturing an external perspective of the vehicle in its environment. Widening the FOV produced the greatest performance benefit; however, if the FOV cannot be widened, then capturing an external perspective may facilitate certain aspects of navigation. Another concept, "Perspective Folding" [105], folds the display screen around the remote operator and maps camera sensor outputs in order to embed the operator in the scene. This approach captures and presents some of the many cues that peripheral vision and optic flow contribute to locomotion, perception of self-motion, and awareness of the 3D environment.

A solution to manage video quality includes the *Maintain Video Quality Tool*, which allows operators to define a minimum desired video quality based on window size (in pixels) divided by the target area "footprint" size (in meters) and the system preserves quality by increasing the window size or changing the zoom factor [84].

2.3.5 Equipment Workload Drivers: Link

An unmanned system command, communication and control link can be broken down into four basic elements: (1) telecommand or uplink, (2) telemetry or downlink, (3) communication links, and (4) payload links [32]. Link characteristics including bandwidth, latency and reliability have been shown to impact operator workload [111].

Latency, or delay between operator input and a vehicle response can range from hundreds of milliseconds to several seconds [32] [112], or even tens of minutes in the case of planetary rovers [53]. In general, as such control lag increases, so does the workload required to control teleoperated systems [16,21]. Under such conditions, operators must estimate the vehicle's future state based on current display feedback and judgments about the control input outcomes. When latency is greater than a few hundred milliseconds, operators using manual control [56] adopt a move-and-wait strategy characterized by small control inputs, followed by waiting for feedback, followed by small inputs [21] [113] [114], all of which may increase workload.

Low update rates, long communication delays, and complete loss of communications lead to discontinuous and slow visual and sensory feedback in response to operator control inputs. This situation can cause instability in manual UAV control or camera image control. Again, operators typically adopt a move-and-wait strategy under such circumstances [50]. Furthermore, in instances when communications are not continuous or there is severe latency, operator workload will increase due to additional information processing to interpret the state of the world based on discontinuous and/or out-of-date information.

Link unreliability is an issue for all unmanned vehicle domains. Control links are not 100% reliable. Link management tasks, including maintaining awareness of link strength and latencies as well as preparing for potential link-loss, especially during control handovers and when operating towards the limits of a signal, can contribute to operator workload [32]. These link management tasks increase visual monitoring load and the need for advance planning.

2.3.6 Moderating Workload: Equipment/Link

Predictive displays may effectively mitigate challenges associated with latency [112] [115] [116] [117]. Such displays minimize the impact of communication delay by simulating a 'phantom' vehicle that anticipates real vehicle motion produced by an operator's control actions [68] [112] [117]. However, predictive displays require accurate models of vehicle motion, which often are unavailable for varied terrain [117]. More advanced automation may be appropriate, such as autonomous waypoint following, in which an operator transmits a list of waypoints that a vehicle can track [44]. Alternatively, "safeguarded teleoperation" [118] may be considered when the control of a remote vehicle is shared by the human and the onboard software. The operator has full control over vehicle motion for benign terrains, while hazardous situations will trigger the onboard software to override the operator's commands to ensure safe driving [117]. The use of control-gain scheduling software can be used to manage the impact of operator control actions on remote vehicle responses under degraded communication link quality of service conditions [119]. The mediating software (middleware) directly relates real-time control link conditions to control gain adjustments in order to maintain vehicle safety and performance under teleoperated modes during severe latency in common terrain navigation.

Link-loss programs allow a vehicle to continue on a safe trajectory, return home, or land when the link is lost [32]. However, such programs can *contribute* to workload by requiring that an operator review and verify the appropriateness of an evolving context during mission performance. Interface support, such as allowing an operator to predict or extrapolate vehicle position over time (provided no inputs are made) or visualize the outcome of a link loss program may moderate operator workload. Similarly, development of an advance mission rehearsal capability or "what-if" scenario simulation can be used to verify the utility of a link-loss program under specific operational conditions. When link unreliability is a primary source of operator workload, increasing automation and autonomy may mitigate workload [120] [121].

2.4 Operator Characteristics

The unmanned system operator represents the final major class of workload driver. Again, workload drivers are considered to be aspects of a mission context, which cannot be manipulated by a systems designer. Technically speaking, operator skill sets can be controlled through operator selection; however, the purpose is to define how design can be facilitated to accommodate operators as opposed to requiring an operator to accommodate a design. When operator characteristics are crossed with other types of workload drivers, workload outcomes can be magnified. Consequently, unmanned vehicle designers must accommodate differences in operator characteristics, rather than constraining the operator selection process. Operator characteristics that can influence workload include proficiency and individual differences (Table 5).

Table 5. Operator Workload Drivers

Operator Workload Sub-class	*Examples*
Proficiency	• Insufficient unmanned vehicle operational experience (in general and with specific model) and training. • Low task experience and familiarity. • Lack of related experience (e.g., video game, navigating, orienteering). • Insufficient training. • Insufficient operational setting familiarity.
Individual Differences	• Visual limitations: acuity, contrast sensitivity color/night blindness. • Cognitive limitations: poor perceptual speed, spatial ability, attentional control, spatial reasoning. • Memory deficits. • Psychomotor limitations—e.g. reaction time. • Poor problem solving abilities. • Low risk tolerance.

2.4.1 Operator Workload Driver: Level of Proficiency

Operator proficiency in controlling an unmanned vehicle is driven by operational experience, familiarity, and training. Experience encompasses knowledge of an operating environment, such as landmarks, terrain and airspace restrictions, as well as knowledge of unmanned vehicle control in general, and specific model and control station features. Operational familiarity refers to how frequently the human operates the vehicle. Intermittent usage, with long gaps between uses (e.g., bomb squads) can lead to skill degradation. This situation is true across the vehicle domains, such as manned aircraft flight in which manual flight skills degrade, in part, due to automation of flight control functions [122]. When operators lack proficiency, workload may increase. In fact, operators with less experience controlling unmanned platforms experienced higher levels of workload [57].

2.4.2 Moderating Workload: Operator Proficiency.

Clearly, effective operator training with a vehicle and mission is the most direct means of moderating workload due to lack of proficiency. However, the Playbook-enhanced Variable Autonomy Control System (PVACS) is an example of interface design technology that was developed to mitigate workload in operators with limited training and experience [123]. PVACS permits commanding a complex, high-level play (a function or behavior, such as “track target” or “watch perimeter”) via fast and simple actions. The operators do not need to be extensively trained or rated for a specific UAV, but instead only require training to deliver plays via the interface and the meaning of the various system plays [123]. Moreover, calling plays greatly reduced the workload associated with planning for and controlling multiple UAVs. Consequently, this approach may also mitigate operator workload resulting from temporal demands and task structure.

Geofencing may be used to prevent vehicles from entering restricted or dangerous areas; thus, off-loading workload from the human operator to maintain awareness and mitigating workload associated with insufficient familiarity with the operational setting [48] [49]. Automated “safeguarding” systems can moderate workload by reducing the need for continuous vigilance of hazards and compensating for poor proficiency due to training, experience, etc. [118] [124]. The gain-scheduling middleware [119] can account for operator fatigue or lack of alertness when commanding vehicle maneuvers. This technology is essentially a control mode "look-up table" that can be yoked to real-time measures of operator fatigue for moderating vehicle responsiveness to control action.

Additionally, forms of adaptive automation can address dynamic changes in operator functional state [125]. Operator task overload may occur due to demands in information acquisition and analysis as well as decision making and control actions. In a separate study, adaptively applying automation to the various information processing functions, based on secondary task performance measures of operator workload, revealed differential effects on primary task performance and workload [126]. The operators were more effective in using adaptive automation applied to sensory (information acquisition) and psychomotor information-processing functions (control action) than to adaptive automation applied to cognitive functions (information analysis and decision making. It was also found that adaptive automation in a simulated air traffic management task lead to superior performance and reduced operator workload compared to completely manual control.

2.4.3 Operator Workload Driver: Individual Differences

Individuals differ on a wide range of factors that impact their ability to operate unmanned vehicles including perceptual (e.g. visual acuity, contrast sensitivity, field of view, depth perception), cognitive (e.g., attentional control, spatial ability, perceptual speed, mental rotation, memory, problem solving abilities [71]), and sensorimotor capabilities [127] as well as personality traits, motivational states, and emotional states [128]. A full accounting for all of these factors is beyond the scope of this paper, however, we focus on one cognitive capability, spatial ability, as an example to demonstrate the relationship between individual differences and workload.

Spatial ability refers to the ability to navigate or manipulate objects in a 3-D environment [129] and has been found to be a significant factor in visual display domains, and tasks that involve multitasking, navigation, and visual search [71]. Much research (e.g., [129] [130] [131] [132] has shown that operators with higher spatial ability (i.e., mental rotation, spatial visualization, and spatial memory) perform better on tasks such as navigation, target identification and detection times. The effect of spatial ability on workload has been inferred by performance on secondary tasks, a commonly used objective measure of workload. For example [131] showed degraded performance on a secondary task (time to respond to warnings) for those with lower spatial ability when controlling multiple (five) unmanned vehicles. The authors suggest that the participants with lower spatial ability found it difficult to schedule attention between the secondary task (responding to warnings) and the primary task (vehicle control).

2.4.4 Moderating Workload: Individual Differences.

Mitigating workload attributed to individual differences requires careful customization of system information presentation to address each operator's capabilities. Continuing with the example of the effect of spatial ability, research has shown that interface design can be used to moderate performance decrements seen in operators with low spatial ability. For example, the performance gap between operators with high and low spatial ability was reduced by the presence of aided target recognition capabilities delivered either through tactile or tactile plus visual cueing [132]. Further it was found that those with higher spatial ability scores tended to rely on the tactile display to help them with the visually demanding task, more than those with lower spatial ability who preferred the visual cueing. The author pointed out that this was consistent with the finding [133] that those with lower spatial ability tend to rely on iconic imagery, while those with higher spatial ability tend to prefer using spatial-schematic imagery when solving problems. One key task component that appears to cause the difference between the high and low spatial individuals' task performance is the ability to construct a spatial mental model of embedded information [134]. When users were provided with interface designs that eliminated the need to construct a visual mental model of the structure of a menu system, the performance difference between low- and high spatial ability was eliminated. The authors concluded that visualization techniques can be used to enhance information search performance in individuals with low spatial ability.

Another approach to moderate individual differences may be in the form of either adaptable or adaptive automation. Various forms of adaptable automation, or dynamic modes of automation invoked at operator discretion, have been investigated for aviation related tasks. One study [135] compared adaptive automation (system invoked control modes) with adaptable automation and manual control of a flight path-tracking task with simultaneous performance of engine status monitoring and fuel resource management tasks. The adaptive automation increased operator situation awareness and performance for individuals who tended to be more complacent in their use of automation. Adaptable automation was superior to manual control, in terms of performance, but did reveal higher subjective workload.

3. CONCLUSION

In the context of complex human-machine systems, workload is the interaction of multiple contextual variables and a human operator's perception of those variables. In this paper, we developed a taxonomy of workload drivers to support identification of the contextual variables that contribute to operator demands in highly automated and complex systems. Specifically, we identified a set of drivers that may be common/consistent across various types of unmanned vehicle systems. The degree of workload demand imposed by these drivers may vary during operations and have a variety of impacts. Beyond this, we contend that workload drivers may be moderated by various technologies, including automation and methods of automation presentation or interface design.

This review demonstrates that workload is a function of a large number of contextual variables, at least for unmanned system operations. Beyond the potential impact of individual drivers on operator workload, it is important to consider that workload effects may be inflated by the presence of multiple drivers in a particular application scenario. For example, the interaction between route complexity and task precision increases operator workload associated with complex route navigation. However, such precision requirements may pose lower workload for less complex routes. Depending on the context, such factors may contribute to operator perceptions of long-duration underload, long-duration overload, or periods of underload marked by brief spikes of high workload.

One challenge that remains is to determine how to integrate these variables into predictive models of workload that can be used as a basis for complex systems design. An important aspect of this challenge is that the relative importance of drivers may vary as a function of changing contexts and changing operator states in response to on-going fluctuations in demand (workload). For example, as task load increases, operators may adopt adaptive control strategies to offset performance consequences and to maintain workload within a manageable range. Alternatively, operators may change their performance criteria, off-load tasks to other personnel, or engage automated subsystems in order to allocate attention to critical task components [136] [137]. As noted in the moderators listed throughout the review, operators may also make use of adaptable or adaptive automation capabilities that can be conditioned to real-time operator states. Consequently, the presence and relative influences of each type of driver can change from moment-to-moment in systems control as well as the nature of interaction among drivers, such as the compounding effects of operator characteristics on all other drivers. This situation makes any workload model proposition very complex and dynamic in nature. Context-dependent modeling is necessary to address the above issues.

With identification of a broad set of variables that contribute to workload in unmanned systems, future research also needs to focus on the challenge of how the drivers interact in unmanned vehicle systems to contribute to operator load. The potential impacts that we identified for various levels of demand for each type of driver do not account for complex interactions effects among two, three or more demands being present in an operational state. There is also a real need to identify operator workload underload and overload thresholds that will be perceived as unacceptable by unmanned systems operators, in an *a priori* fashion, as a potential basis for effective control mode management in real-time.

The present research is expected to advance the basis for human workload modeling, with the potential for quantification in absolute terms. Such a model will have substantial utility as a basis for addressing workload "bottlenecks" in complex unmanned systems and supporting more effective and efficient UAV, UGV and UUV designs. In particular, the taxonomy of workload drivers and moderators that we have presented may advance the consideration of workload in system design.

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