

Ch. 12. A Theoretical Approach to Management of Limited Attentional Resources to Support the m:N Operation in Advanced Air Mobility Ecosystem

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Abstract

Advanced air mobility (AAM) technologies incorporate increasingly autonomous systems that allow fully remote, independent, and intelligent operation of air vehicles to support the transportation of goods and passengers within and across urban and rural areas. With a myriad of automated technologies enabling the AAM ecosystem, the human operator's role will likely be a passive supervisory monitor of the air vehicles, involving increasingly fewer humans (m) that manage many more autonomous systems (N), or $m:N$ operations. Unfortunately, the human performance literature suggests that human operators will exhibit poor supervision of numerous autonomous agents due to the limits of attentional resources in the operators. In the general human information-processing model, a human operator exercises a limited pool of attentional resources to engage various information-processing stages including detecting, perceiving, comprehending, and predicting objects around them. Yamani and Horrey (2018) expanded the human information-processing model to characterize a tradeoff between information-processing demand and resource relief that automation brings in the context of automated driving. In their model, a driver interacting with an automated driving system is assumed to reallocate resources "freed" by automation to support other information-processing stages required for successful task performance. A future AAM ecosystem enabled by an orchestration of advanced automated systems, however, requires a single operator to interact with more than one air vehicle with varying levels and degrees of automated systems, making the traditional framework of human-automation interaction insufficient. To address this gap, we provide a review of the literature on situation assessment and trust, two constructs identified as critical for a fuller understanding of intimate and intricate interactions between a human operator and multiple air vehicles equipped with increasingly autonomous systems. Then, we propose an expansion of Yamani and Horrey's (2018) model to motivate systematic research on the human operator's role, identify factors that influence resource allocation and guide human-centered design of an interface supporting the $m:N$ operation in the AAM environment.

Introduction

The implementation of advanced air mobility (AAM) holds tremendous potential for revolutionizing various industries, facilitating efficient transportation of cargo and passengers across urban and rural areas (National Academics of Sciences, Engineering, and Medicine, 2020). For example, healthcare services are expected to leverage AAM technologies to deliver vital medical supplies connecting remote areas more efficiently than other means of transportation (Sigari & Biberthaler, 2021). As AAM technology continues to advance, human operators will rely on increasingly autonomous systems that support varying functions of flight management (Wing et al., 2020). Consequently, an operator's role will likely shift from being an active pilot in command to a passive supervisory monitor of numerous autonomous aircraft producing a reduced ratio of human operators (m) to that of aircraft (N) in the AAM ecosystem (m:N operation; Aubuchon et al., 2022). However, there exist several challenges in m:N operations including the human operator's attentional limit to monitor multiple vehicles equipped with multitudes of automated functions, and the human operator's susceptibility to automation disuse and misuse (Parasuraman & Riley, 1997). To fully enable m:N operations, human factors research focusing on human attentional limits is urgent, particularly to identify factors that determine successful human-AAM technology interaction. The present chapter describes a theoretical framework of human-AAM technology interaction, offering insights into the psychological mechanisms that are critical for enabling m:N operation and future directions for research in this field.

AAM technology and ecosystem

The mission of AAM is the development of safe air transportation systems that are affordable and accessible to the general public (Patterson, 2021). AAM operations will be enabled by the development of systems including, but not limited to, electric propulsion, sensor, and control systems (National Academics of Sciences, Engineering, and Medicine, 2020). The concept of AAM encompasses a wide range of air vehicles such as small Uncrewed Aircraft Systems (sUAS), large Uncrewed Aerial Vehicles (UAV), and electric vertical takeoff and landing (eVTOL) vehicles (supporting Urban Air Mobility [UAM], or air taxi operations). The evolution of these aircraft will rely on increasingly autonomous systems (National Research Council, 2014) that support varying flight tasks, such as the navigation of vehicles (Chancey et al., 2021). The term 'increasingly autonomous' characterizes technology that spans "the spectrum of system capabilities that begin with the abilities of current automatic systems, such as autopiloted and remotely piloted (non-autonomous) unmanned aircraft, and progress toward the highly sophisticated systems that would be needed to enable the extreme cases" (National Research Council, 2014; p. 2). Future AAM operations are expected to achieve full autonomy wherein increasingly autonomous systems pilot an air vehicle with minimal human intervention (Wing et al., 2020). Throughout the current work, the term "autonomy" refers to a characteristic of a system that is viable, independent, and self-governing (Chancey & Politowicz, 2020; Kaber, 2018; Wing et al., 2020). In this regard, the term "increasingly autonomous system" refers to automation that performs a task with more autonomy from human intervention than conventional automation. As AAM systems achieve full autonomy, the human operator's role is expected to shift from a pilot in command to a system operator, and then to a system assistant (Sato et al., 2022). Specifically, we have adopted the following definitions of pilot in command, system operator, and system assistant (see Table 12.1).

Table 12.1. Summary difference between human operator's role in AAM.

Role	Directly Controls Vehicle(s)	Set Goals or Intentions	Human Intervention	Notional Span of Influence
Pilot in Command	Yes	Yes	Human operators do not need to intervene because they are directly controlling the vehicle.	A single human operator directly controls 1 vehicle
System Operator	No	Yes	Yes	A single human operator manages 10+ vehicles
System Assistant	No	No	Only during off-nominal situation (ex. system error)	Human operators cannot influence highly automated vehicles due to cognitive limitations.

Pilot in command “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” (Sato et al., 2022, pp. 29). A system operator “actively sets a goal or intention of the aircraft but does not have the ability to directly control the aircraft” (Sato et al., 2022, pp. 29). The notional span of influence for a system operator is set at 10+, which is based on previous work indicating a single operator could manage approximately 10-15 vehicles (Cummings et al., 2014; Galster et al., 2001). A system assistant “assists multiple aircraft without active control or management, with the exception that they intervene in off-nominal scenarios such as critical system failure or passenger emergency” (Sato et al., 2022, pp. 29). As indicated in Table 12.1, the number of vehicles that human operators can influence (i.e., span of influence) varies across different human responsibilities. These human responsibilities correspond to either Simplified Vehicle Operation (SVO) or Remote Vehicle Operation (RVO; see Chancey et al., 2021; Wing et al., 2020). SVO is defined as “the use of automation to reduce the number of skills a pilot or operator of an aircraft must acquire to achieve the required level of operational safety” (General Aviation Manufacturers Association, 2019, pp. 2). RVO is characterized as an operation where “aircraft are remotely controlled by some combination of one or more humans piloting a single aircraft or operating/managing many aircraft, with varying degrees of automation support” (Chancey & Politowicz, 2020, pp. 1). The concept of RVO ranges from a single pilot remotely

operating a single aircraft, to multiple pilots remotely operating a single aircraft, and to multiple pilots remotely operating multiple aircraft.

The m:N operational paradigm envisioned in AAM requires fewer human operators to manage a number of aircraft supported by higher levels of automation simultaneously. Unfortunately, though, theories of applied human performance indicate that human operators' capacity limits severely constrain their performance and interaction with multiple dynamic air vehicles. Two points are noteworthy. First, human operators are theorized to have limited attentional resources, which support a stream of information-processing stages (Kahneman, 1973; Wickens et al., 2021; Yamani & Horrey, 2018). Second, human operators can exhibit counterproductive behaviors in tasks supported by automation such as disusing reliable automation and misusing unreliable automation (Parasuraman & Riley, 1997). These counterproductive behaviors may be explained by a human operator's trust in automation. The following sections provide a literature review on these points and propose a novel theoretical model that characterizes human-autonomy teaming (HAT) applicable to m:N operation. Note that a list of factors included in the proposed model is not meant to be exhaustive, as other unexplored factors can still influence HAT and human-automation interaction in m:N operation.

Theories of Attention Allocation

Several theoretical frameworks in human-automation interaction lend support for describing a human operator's limited attentional capacity (Parasuraman et al., 2000; Wickens et al., 2021; Yamani & Horrey, 2018). Wickens et al. (2021) proposed that information is processed through a series of different human information-processing stages including sensory processing, perception/working memory, decision-making, and action implementation. Attentional resources are theorized to act as a "fuel" that activates and supports different stages of human information processing based on the resource allocation policy. Kahneman (1973) defined attentional resources as a unitary pool of mental energy that is distributed across different stages of human information processing. In an attention-demanding environment, multiple tasks compete for limited attentional resources. Thus, human operators are required to efficiently distribute attentional resources to satisfy each task demand. Furthermore, Wickens et al. (2021) postulated that human performance depends on the correspondence between the number of attentional resources allocated and the attentional demand imposed by the task. Specifically, human operators will exhibit successful task performance when trained human operators supply enough attentional resources to meet the attentional demand of a task (e.g., attentional resources are greater than task demand). Alternatively, human operators will exhibit poor task performance when the attentional demand exceeds the number of attentional resources supplied (e.g., attentional resources are less than or equal to task demand). Unfortunately, many professional and operational environments impose greater processing demand than one operator may possess, requiring the use of automation to support their performance. Automation consists of different functions that support corresponding stages of human information processing at varying levels of automation based on the attentional demand of the task including information acquisition, information analysis, decision selection, and action implementation (Parasuraman et al., 2000). Later, Yamani and Horrey (2018) proposed a theoretical model of human-automation interaction by integrating Wickens et al. (2021) and Parasuraman et al.'s (2000) theoretical framework to characterize the remobilization of attentional resources that are "freed up" by automation in a multitasking environment (Figure 12.1).

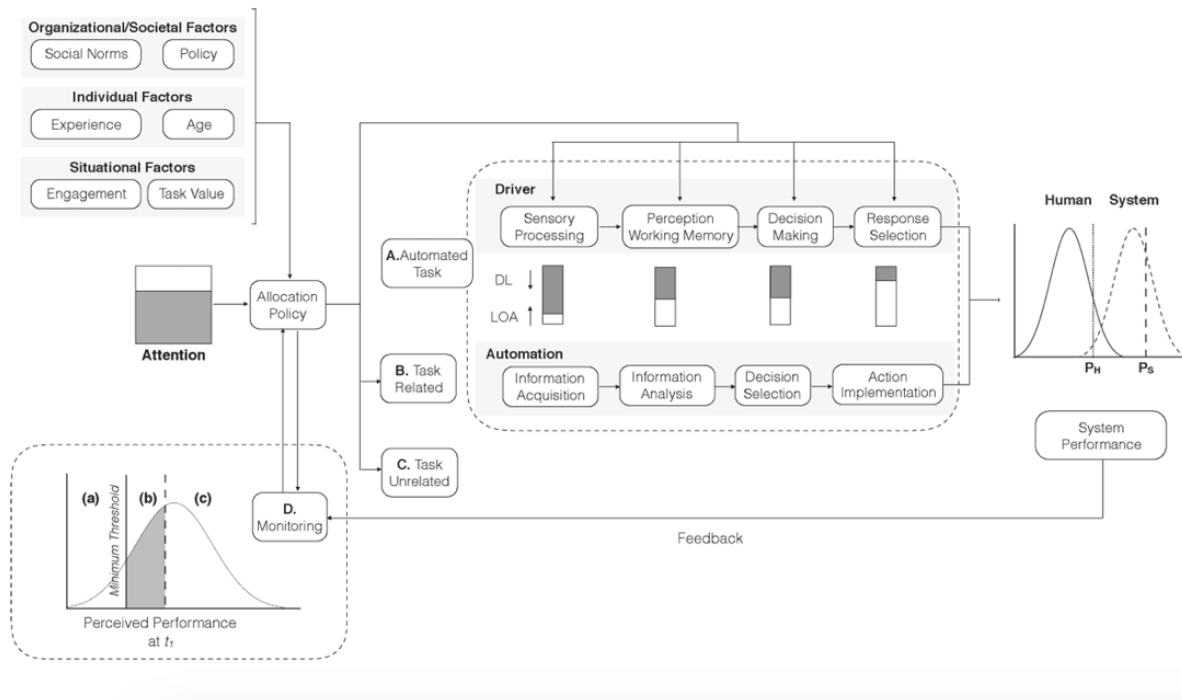


Figure 12.1. Yamani and Horrey's (2018) theoretical model of human-automation interaction.

As indicated in Figure 12.1, the theoretical model depicts a human operator concurrently performing a task with the assistance of an automation (i.e., automated task), a task that is related to the automated task (i.e., task related), a task that is unrelated to the automated task (i.e., task unrelated), and a task that requires a human operator to monitor the automation (i.e., monitoring). Each task will compete for limited attentional resources to support one to all stages of human information processing. Following Wickens et al.'s (2021) model, the attentional resources support different stages of human information processing depending on the attentional demand and the resource allocation policy. When a primary task is automated, the automation supports one or more stages of human information processing at varying levels of automation (Parasuraman et al., 2000). Consequently, the resource allocation policy will allow the strategic mobilization of attentional resources to the secondary task because the greater the level of automation becomes, the more resources become available for reallocation. Furthermore, Yamani and Horrey (2018) proposed that the resource allocation policy is influenced by three different sets of global factors including situational factors, individual factors, and organizational/societal factors. Situational factors refer to factors that have influence on the immediate interaction with a task and encompass different properties of the task, such as the engagement of the task and the value of the task. Individual factors concern different aspects of human operators such as age and experience. Organizational/societal factors represent aspects within the organization or workplace that influence attention allocation such as social norms and organizational policy.

Finally, the theoretical model consists of an output that depicts the operator's perception of human-automation performance over time where P_H represents a hypothetical human performance level without automated aid whereas P_S represents a hypothetical human-automation performance level. This model operates as a closed-loop mechanism where the

human operator compares the output performance to the desired level of the joint human-automation performance. Consequently, human operators can adjust their resource allocation strategy based on the alignment between perceived and desired human-automation performance. The model assumes that the operator possesses a threshold of human-automation performance above which the operator perceives the performance acceptable. When the human-automation performance falls below the minimum threshold (i.e., within area A. Automated Task), human operators could either allocate more attentional resources to a task (i.e., automated task or task related) or assign more tasks to an automated system. Conversely, if human-automation performance slightly exceeds the minimum threshold (i.e., within area B. Task Related), human operators could either allocate more attentional resources for monitoring or perform the task manually by disengaging the automation (i.e., automation disuse). Finally, when human-automation performance significantly surpasses the minimum threshold (i.e., within area C. Task Unrelated), human operators could allocate attentional resources to unrelated tasks (i.e., automation misuse).

The literature in Cognitive Psychology informs that human operators can track only a limited number of objects in space simultaneously (Alvarez & Franconeri, 2007; Bisseret 1971; Cumming & Guerlain, 2007). For example, Alvarez and Franconeri (2007) examined the participant's capacity to track multiple moving objects under varying speed limits of the moving objects. Results indicated that the participants have a maximum tracking capacity of 8 objects. Interestingly, the participant's maximum tracking capacity is dependent on the speed of the moving objects. Specifically, the participant's maximum tracking capacity can gradually decrease as the speed of the moving objects increases. Alvarez and Franconeri (2007) indicated that attentional resources are depleted as the number of tracked objects increases as well as the complexity of the objects increases. Alternatively, Bisseret (1971) examined air traffic controllers' (ATC) working memory capacity across varying levels of expertise. Results indicated that highly experienced ATCs have a working memory capacity of approximately 10 chunks. This estimate is close to what is reported in Miller's (1956) notable work of 7 objects plus or minus 2. Finally, Cumming and Guerlain (2007) developed a model that estimated U.S. Navy personnel's capacity to monitor and control missiles. Results indicated that task performance and situation awareness degraded when monitoring 16 missiles compared to when monitoring 8 missiles and 12 missiles. Furthermore, these measures were comparable between monitoring 8 missiles and 12 missiles indicating that the participant's monitoring capacity ranges from 8 to 12 objects. However, these divergent results should be interpreted with caution. That is, participants in Alvarez and Franconeri (2007) tracked objects without a context to form a meaningful mental model that allows the comprehension and prediction of movements, whereas Cumming and Guerlain (2007) did allow the construction of a mental model. Therefore, it is possible that humans can track moving objects up to 12, but if an operational context that allows them to develop mental models is not available, then the number will significantly drop potentially to 5.

What is needed is a systematic investigation of factors that determine capacity limits of human operators that allow accurate tracking of multiple objects, each of which requires different amounts of attentional resources due to differing levels of automated support. Nonetheless, the Yamani-Horrey (2018) model was developed to account for human performance in the context of automated driving where a single operator interacted with a single automated driving system in a standard driving task. Therefore, the model is expanded below to allow distribution of attentional resources to multiple aircraft supported by different levels of automation along with the assessment of situations in confined air spaces. However, it is

noteworthy that the literature on human-automation interaction indicates a critical role of automation trust in shaping successful teaming between a human and increasingly autonomous systems.

Trust in Human-Automation Interaction and Human-Autonomy Teaming

Trust is a construct that is known to influence human-automation interaction (Chancey et al., 2017; Hoff & Bashir, 2015; Karpinsky et al., 2018; Lee et al., 2021; Lee & See, 2004; Long et al., 2022; Muir & Moray, 1996; Sato et al., 2020; Sato et al., 2023c; Yamani et al., 2020). Trust is defined as “an attitude that an agent will help achieve an individual’s goal in a situation characterized by uncertainty and vulnerability” (Lee & See, 2004, p. 51). The concept of automation trust originated from interpersonal trust research (Barber, 1983; Kramer, 1999; Rempel et al., 1985; Mayer et al., 1995). For example, Muir and Moray (1996) proposed a theoretical framework of trust in automation by integrating theories of interpersonal trust (Barber, 1983; Rempel et al., 1985). Specifically, Muir and Moray’s (1996) theoretical framework postulated that trust toward automation is driven by three expectations including persistence, technical competence, and fiduciary responsibility. Persistence refers to the expectation that natural and moral law remain constant. Technical competence refers to the expectation that automation is capable of task performance. Fiduciary responsibility refers to the expectation that automation is obligated to complete a task. Furthermore, Muir and Moray’s (1996) work suggested that trust developed from faith to dependability, and then to predictability. Predictability refers to the degree in which the automation’s behavior is consistent and desirable. Dependability refers to the extent to which the human operators rely on automation. Faith refers to the degree of certainty towards the future state of automation.

Our recent works, however, failed to replicate this finding (Long et al., 2022; Lee et al., 2021). Later, Lee and See (2004) proposed a conceptual model that describes the dynamic process involving trust in automation. According to Lee and See (2004), the development of trust is accounted for by the interaction of the automation’s characteristics, appropriateness of trust, and contextual factors. Specifically, trust in automation is based on three information sources including performance, process, and purpose. Performance-based trust is driven by the human operator’s perception of the automation’s behavior. Process-based trust is developed while accumulating information on the automation’s mechanism. Purpose-based trust arises from understanding the system designer’s intention for developing the automation. These information sources are accumulated to develop appropriate trust in automation. The appropriateness of trust in automation is described by the calibration, resolution, functional specificity, and temporal specificity. Calibration is the extent to which the human operator’s trust matches with the capability of automation. Resolution is the extent to which the changes in the human operator’s trust correspond to the changes in the automation’s capability. Functional specificity describes whether a human operator’s trust reflects the capability of automation’s subfunction (i.e., high functional specificity), or the entire system (i.e., low functional specificity). Temporal specificity describes whether a human operator’s trust reflects immediate changes in automation capability (i.e., high temporal specificity), or long-term changes in automation capability (i.e., low temporal specificity). In sum, trust is a critical construct that determines human-automation interaction, and its understanding has been shaped by various theoretical frameworks and models.

Recent models of human-automation trust have built upon and adapted earlier frameworks, expanding our understanding of trust in automation (e.g., Hoff & Bashir, 2015). Yet our primary interest is in Lee and See’s (2004) notion of the three bases of trust in automation

(i.e., performance, process, and purpose). Specifically, our studies attempted to explore the trajectory of human-automation trust based on these three bases of trust in automation as described below.

To explore the development of trust across three information sources, we initially investigated different factors that influenced the three bases of trust in automation (Chancey et al., 2017; Karpinsky et al., 2018; Sato et al., 2020; Sato et al., 2023a; Sato et al., 2023c; Sato & Yamani, 2023). For example, Karpinsky et al. (2018) asked undergraduate students to concurrently perform the tracking task and the system monitoring task in the Multi-Attribute Task Battery-II (MATB-II; Santiago-Espada et al., 2011). The system monitoring task was supported by imperfect automation with a reliability of 70%. The automated aid made an incorrect response by providing either false alarms (i.e., the aid detected errors when the engine was in a normal state) or miss events (i.e., the aid did not detect errors during an engine malfunction). Task load was manipulated by changing the difficulty of the tracking task across the experimental trials (i.e., high or low difficulty). Results indicated that participants rated lower performance- and process-based trust under high task load conditions where the tracking task demanded more attentional resources. In addition, eye movement data indicated that participants visually sampled less frequently on the automation under high task load conditions. These findings suggest that participants may misperceive the automation's behavior due to inefficient sampling of the automation. However, Karpinsky et al. (2018) did not provide empirical evidence on the relationship between trust in automation and attention allocation.

In Sato et al.'s (2023b) recent work, they examined the relationship between the three bases of trust and attention allocation by conducting a meta-analysis across three experiments (Sato et al., 2020; Sato et al., 2023c; Sato & Yamani, 2023). Results indicated a negative correlation between performance-based trust and attention allocation. This suggests that operators displaying high performance-based trust made less frequent visual sampling of the automation. Furthermore, the findings support Hoff and Bashir's (2015) notion of dynamic learned trust. That is, the automation's performance impacts human-automation trust when operators interact with the automation. Although these works examined trust in automated systems, future AAM operations will employ autonomous systems that achieve full autonomy. Thus, it remains an empirical question of whether and how human trust evolves and supports HAT.

Research on HAT focuses on the coordination between the human operator and an autonomous agent (Demir et al., 2021). Specifically, we define HAT as "...a distinguishable set of two or more agents (human and machine) that interact dynamically, interdependently, and adaptively toward a common goal/objective/mission" (Chancey et al., 2023, p. 2; adapted from Salas et al.'s [1992] definition of human teams). According to Shively et al.'s (2018) conceptual model of HAT, there exists three principles including, 1) bi-directional communication between human operator and autonomous agent; 2) transparency of an autonomous agent; and 3) task allocation by the human operator. There has been a growing number of research studies that examined trust in HAT (Cohens et al., 2021; Demir et al., 2021; Graham et al., 2022; McNeese et al., 2019). Specifically, these works examined how the coordination of communication between the human operator and an autonomous agent influences the development of trust. For example, Demir et al. (2021) examined the development of trust in HAT across different system failures (i.e., automation, autonomy, and cyber-attack failure) by employing a wizard of oz paradigm. Specifically, two participants communicated with an experimenter who acted as an autonomous pilot within a flight simulated task environment (i.e., Cognitive Engineering

Research on Team Tasks RPAS Synthetic Task Environment). Results indicated that human operators' trust degraded over time when an autonomous pilot provided incorrect information or made an incorrect action (i.e., autonomy failure). Indeed, our team postulates trust as a critical factor in m:N operations (Chancey et al., 2023; Chancey et al., 2021; Chancey & Politowicz, 2020; Sato et al., 2023a; Sato et al., 2023b). Yet, differences between trust in HAT and trust in human-automation interaction remained uncertain.

Kaber (2018) proposed a conceptual model that distinguishes automation and autonomy (i.e., autonomous systems). Specifically, an agent achieves full autonomy when all three dimensions of autonomy reach the highest level (i.e., viability, independence, and self-governance). Viability pertains to the capability of the agent to execute fundamental tasks in the environment. Independence refers to an agent's ability to accomplish a task without human intervention. Self-governance is defined as an agent's capacity to set up goals and devise strategy for its operation. Furthermore, an agent is considered an automation when one of these dimensions are violated. For instance, when a person uses a Rumba to clean the floor in a kitchen, it is considered an autonomous system (i.e., achieves full autonomy) because it can clean in the kitchen and does not require human intervention. However, if a person places a Rumba in the backyard, it is considered automation because it cannot clean in the backyard (i.e., violation of viability), and it requires human intervention (i.e., violation of independence). Thus, this conceptual framework is dependent on a situation where the machine of interest is used and designed to be used.

In the context of AAM, it is expected that many of the technologies supporting m:N applications will possess all three dimensions of autonomy at the highest level. In Sato et al.'s (2023a) recent work, they applied Kaber's (2018) conceptual framework to conduct a survey study investigating trust in HAT and trust in human-automation interaction. Specifically, we asked participants to read four vignettes that each describe a drone (i.e., autonomous drone that possesses all three dimensions of autonomy; an automated drone without viability; an automated drone without independence; or an automated drone without self-governance). After reading each vignette, participants rated trust towards a drone by completing two trust questionnaires (Chancey et al., 2017; Jian et al., 2000). Results using Jian et al.'s (2000) trust questionnaire indicated that trust scores were highest in a scenario where humans use an autonomous drone or a drone without human intervention for navigation. In the context of AAM, trust is expected to be a driving factor in m:N operations (see Chancey et al., 2023), although extensive research is necessary to understand the relationship between trust and attention allocation in HAT. Thus, our work proposes a theoretical model of human-AAM technology interaction based on the human-automation interaction literature. In sum, our proposed model adapts Yamani and Horrey's (2018) model to characterize the human operator's attentional allocation strategy in an AAM environment involving m:N operations. Furthermore, we consider potential constructs that influence attention allocation across multiple vehicles, including trust and situation assessment. Ultimately, our proposed model will offer guidance for systematically exploring HAT in human-AAM technology environments.

A model of human-AAM technology interaction centering on human attentional limits

Yamani and Horrey's (2018) model assumes that a human operator 1) allocates limited attentional resources based on resource allocation policy to support a stream of information-processing stages that are required for completing a given task at hand; and 2) *re*-allocates the resources that are "freed" by automation corresponding to specific stages and levels of its

support. Figure 12.2 illustrates hypothetical resource demands across the four information-processing stages and corresponding automated assistance according to Parasuraman et al. (2000). Note that increased automation features allow operators to save corresponding amounts of resources at each information-processing stage. It is assumed that the operator redistributes recovered resources to other tasks, related or unrelated to the primary task.

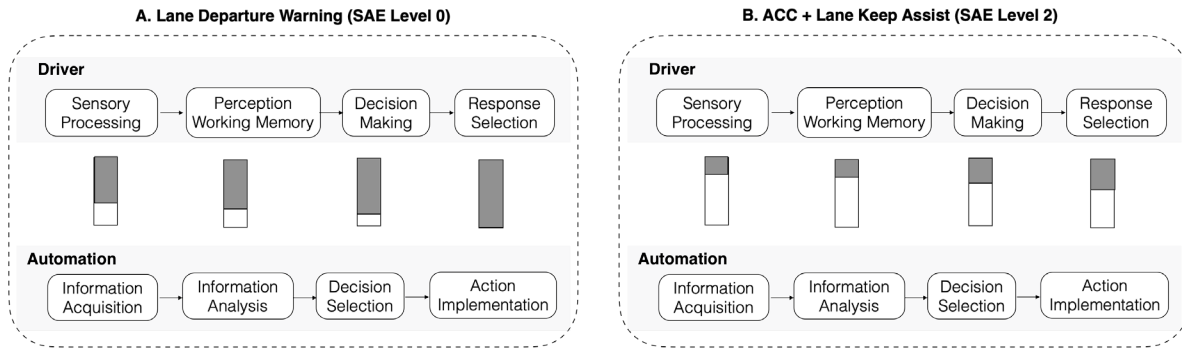


Figure 12.2. Hypothetical resource demands for each of the four information-processing stages in a driver assisted by lane departure warning (Society of Automotive Engineers [SAE] Level 0 automation; left, A) and adaptive cruise control (ACC) and lane keep assist (SAE Level 2 automation; right, B).

In the ground transportation domain, the model partially explains why drivers often engage in task-unrelated thoughts (TUTs) (Yanko & Spalek, 2014). For example, the driver may have a liberal decision cutoff that biases the allocation policy to prioritize driving-unrelated tasks over the primary driving task. Recent human-in-the-loop driving simulation experiments show empirical support for this prediction: Drivers of level-2 vehicle automation (an automated driving system that assumes “humans” are driving) paid more attention to road environments during piloting the automation than those of level-3 vehicle automation (an automated driving system that assumes the “system” is driving) (Unverricht & Yamani, in preparation). This implies in general that, depending on levels of automation and expectations, where drivers of L2 vehicle automation were expected to attend to the road while those of L3 were not, drivers can remobilize available resources strategically to meet the task demand.

Here, we propose an integrated model of human-AAM technology interactions based on Yamani-Horrey’s (2018) model to guide systematic research on intricate interactions between fewer human operators and more increasingly autonomous systems supporting m:N operations. We assume that 1) a human is a capacity-limited information processor; 2) a human operator is ultimately responsible for the consequences of multiple air vehicles in their air space; and 3) the human operator is in the loop.

An obvious difference between the context of automated driving and that of AAM is the number of automated systems that a single operator is responsible for. A driver interacts with one automated vehicle at a time, whereas an operator in mature AAM operations will interact with

potentially several air vehicles equipped with automation at various levels. Additionally, levels and degrees of automation can be different between air vehicles and may change dynamically over time, which complicates this modeling effort. In sum, the amount of limited attention given to a particular air vehicle is a function of the number of total vehicles and the level of automation supporting each vehicle, or

$$A_i = f(LoA_i),$$

where A_i denotes the amount of attention demanded by a vehicle i , N represents the total number of air vehicles to be attended, and LoA_i is the level of automation applied to vehicle i . Here, the function, f , between LoA and A needs further empirical exploration to better characterize as a cognitive process such as situation assessment (see below) which may require more attentional resources than sensory/perceptual processes. The amount of attention allocated to each vehicle reduces as the operator divides attention to the total number of air vehicles, N , and as more automated functions are available to the vehicle. Thus, the total amount of attentional demand from an AAM task is the sum of all attentional demands for all the vehicles under supervision, or

$$A = \sum_{i=1}^N A_i.$$

Now, following Wickens et al. (2022), operator performance declines when attentional demands exceed the operator's attentional capacity. Assume that an operator's attentional resources are limited at a certain capacity, C . More formally, thus, an operator can perform the AAM task if $C > A$ whereas their performance declines if $C \leq A$. If $C \leq A$, then to avoid performance decrements, the operator prioritizes vehicles with greater attentional demands.

Situation Assessment

With m:N operations, an operator will be required to monitor multiple air vehicles operated by automated systems. As noted above, though, each operator is subject to capacity limits, which necessitates them to prioritize which vehicles to attend to depending on their attentional demands. Therefore, it is critical for an operator to *assess* each situation in the dynamic AAM environment and to effectively select which vehicle(s) to attend. *Situation assessment* can be considered as the exploration phase in Neisser's perception-action cycle in which an observer samples objects in an environment to develop their schema or mental models (Figure 12.3).

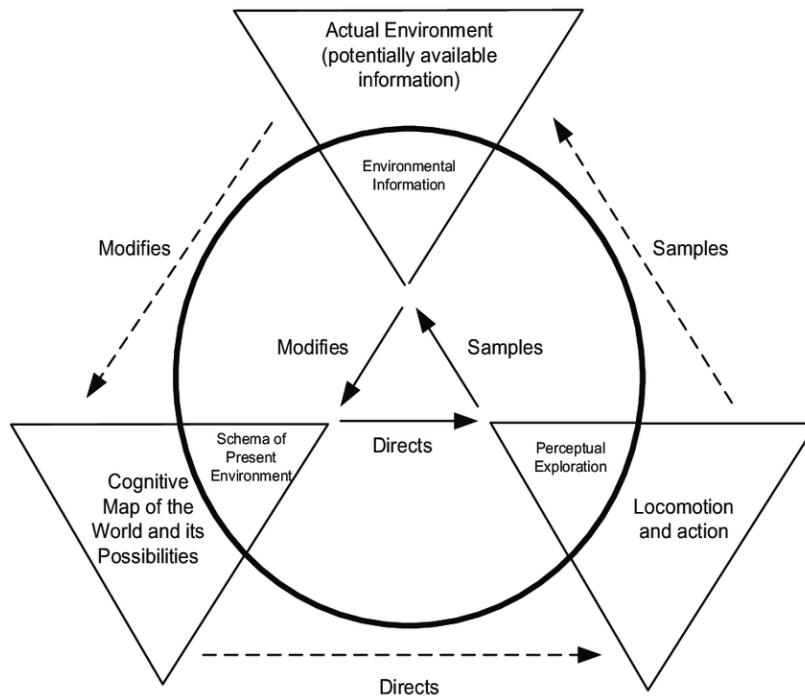


Figure 12.3. Neisser's (1987) perceptual cycle model.

More specifically, Roth and colleagues (1994), in the context of nuclear power operations, listed different types of observable behaviors that result from situation assessment, which are:

- Check for evidence to confirm hypothesis
- Explain observed symptoms
- Identify unexpected plant behavior
- Anticipate future problems
- Search for explanation

where the search for explanation results from:

- Detect abnormal plant behavior
- Identify problems (e.g., sensor failures, plant malfunctions)
- Detect alarms/symptoms that had been missed

In the context of AAM, based on Roth et al. (1994), an operator in the situation assessment phase should allocate attention to vehicles that 1) behave abnormally; 2) report malfunctions or functional failures; or 3) issue an alarm. In fact, air vehicles are expected to carry highly reliable sensors and warning systems, and thus it is likely that an alarm indicating some system malfunction should attract the operator's attention.

It may be possible that the outcome of a situation assessment directly influences the capacity parameter, C , in two ways. First, the ability to anticipate future problems would allow the operator to project the current situation to the future (e.g., Level 3 situation awareness; Endsley, 1995), and thus mentally simulate how air vehicles are traveling in space while the situation unfolds over time. Using the anticipated patterns of air vehicles to track, the operator may expand their capacity and effectively allocate resources to vehicles with less certainty in their projection. Second, improved situation assessment may allow the operators to “chunk” individual elements of information, thereby allowing them to increase their capacity. For example, a group of aircraft can follow the same path for routine delivery of goods where the operator does not necessarily track all the individual vehicles separately, but may monitor them as a group of vehicles, counting as one object. The current model incorporates situation assessment as an intermediary step between attention allocation policy and tasks where the attention resources are eventually allocated.

Trust

As mentioned earlier, trust is one of the most important factors that drives successful interactions between human operators and highly automated systems. Our recent meta-analysis showed a negative correlation between performance-based trust toward an imperfect automated decision aid and percent dwell time (PDT) toward the task involving the automated aid, reflecting a reduced resource allocation (Sato et al., 2023b). However, it is unclear, in m:N operations, whether an operator develops trust toward *each* air vehicle or *all* air vehicles to be monitored. A more recent theory such as system-wide trust (SWT) (Keller & Rice, 2009) may guide our current exploration. In SWT, operators treat multiple individual information sources as one system and display trust toward the system but not to individual sources. However, it awaits empirical investigation whether SWT theory holds in m:N operational environments, because individual air vehicles could operate independent of each other, and the theory assumes that each information source is perceived as part of a larger information ecosystem. As a moment-to-moment situation dynamically changes as each vehicle may adjust its LoA due to external disturbances, such as weather and traffic congestion, it is possible that an operator develops trust in some individual vehicles of lower LoA or when the number of air vehicles under supervision is relatively small. Further development of real-world m:N operational environments along with research is necessary to address these issues.

We assume the SWT theory holds in AAM operations, where an operator develops trust to only a system but not individual air vehicles. Thus,

$$A = -T \cdot \sum_{i=1}^N A_i,$$

where T represents trust toward an AAM system. That is, if trust in the AAM system increases, then the overall attentional demand decreases (Sato et al., 2023b).

Overall description of a model of human-AAM technology interaction

The present model of human-AAM technology interaction mimics the general structure of Yamani-Horrey’s (2016) theoretical model such as the interaction, which is modeled as a product of the allocation of attentional resources to support relevant information-processing stages. Further, the resource allocation is influenced by external factors including sociotechnical factors, individual factors, and situational factors. Additionally, the outcome of the human information processing is rendered as system-level performance which is later evaluated by the

operator for the next iteration of resource allocation. These streams of information processing establish a closed-loop system where information input from the environment influences processing of the information resulting in an action that changes the environment itself.

As described above, our new model features two additional processes, perhaps unique to the proposed AAM technology (Figure 12.4). First, resource allocation depends on the outcome of the situation assessment. Though psychological processes that underlie situation assessment require further research, accurate situation assessment would allow the operator to prioritize resource allocation to aircraft that behave abnormally, malfunction, or issue alarms (or report an urgency such as requesting emergency medical services) while maintaining high levels of situation awareness of dynamic airspace. Presumably, there exists an interplay between bottom-up, or data-driven, processes where signals from aircraft and the environment are processed to develop situation awareness while top-down, or experience-driven, processes where predictable paths and behaviors of aircraft in well-learned scenarios would influence the processing of received information in dynamic AAM environments.

Second, and again, requiring much research in the future, trust in automated or autonomous systems is assumed to influence attention allocation policy. The literature indicates that it is possible that a human operator may form their trust in individual components of a system or a system as a whole. At this point, it is unclear how an AAM operator develops and exhibits their trust toward either an individual air vehicle that receives more attentional resources, or an automated/autonomous system providing support to the overall AAM ecosystem. However, evidence from our own lab indicates some pointers. First, our meta-analytic study, combining eye and trust data across four human-in-the-loop MATB experiments, showed a negative correlation between performance-based trust toward automation and percent dwell time toward a task that is assisted by the automation (Sato et al., 2023b). This implies that, when operators are basing their trust on their perception of the behavior of automation, trust levels are higher when operators do not closely monitor its behavior. However, this relationship was found weaker on process-based trust and not detectable on purpose-based trust, suggesting that trajectories of the three bases of trust are likely different.

Third, our survey study comparing autonomy and three different types of automation with one of viability, independence, and self-governance selectively violated, showed that participants exhibit similar behavioral responses and trust to autonomy and automation without independence in the AAM context. What we do not know is how differential levels of trust across different types of automation or autonomy influence their performance and interaction with air vehicles supported by advanced automated technologies. For example, do operators allocate attention similarly between an autonomous drone and an automated drone, the latter of which lacks independence and requires operators to take over control? Our research on influence of different automation characteristics, capability, and reliability on trust and their resulting performance and behaviors is still in its infancy stage. Nevertheless, the present model provides clear paths toward future systematic research to understand the limitations and capabilities of human operators within a novel AAM environment with ever-increasing automation technologies.

Resource allocation is central to the present model where we underscore influences of external factors. Sociotechnical factors include policies and regulations put forth by regulating agencies such as the Federal Aviation Administration (FAA), and social norms such as industry standards, and where use purposes are accepted and prioritized by society. Individual factors refer to individual differences that influence the capacity limits and resource allocation strategies, such as experience and age. Situational factors include task engagement (Horrey et al., 2017) and task priority (Sato et al., 2023c). A given operational situation may require operators to engage in different aspects of the aircraft or the mission or to prioritize specific aircraft to attend for close monitoring. Note that this list is not meant to be exhaustive but to illustrate the complexity of human-automation interactions and the exemplary and relevant factors that likely influence human-AAM technology interactions.

Conclusion

The present chapter presents a theoretical model focusing on the attentional resource allocation of human-AAM technology interaction enabling m:N operations. Human operators will eventually be responsible for managing multiple vehicles until all aircraft become autonomous. The model assumes that human operators have limited attentional capacity requiring them to assess the dynamic situation of m:N operations in an AAM environment, and support various information-processing stages in the operators. In this situation assessment phase, human operators select vehicles that exhibit system malfunction such as frequent false alarms and improper functioning of AAM technology. Furthermore, the model postulates trust as a critical factor that drives human-AAM technology interaction. Our meta-analysis study (Sato et al., 2023b) indicated a negative correlation between trust and attention allocation, indicating that trust could influence the allocation policy that determines attention allocation.

The main contribution of this theoretical model is that it offers guidance for exploring potential psychological factors that are essential in m:N operation. Yet, within the model, several research areas are identified for further investigation. First, it is unclear how AAM operators perceive trust toward multiple autonomous vehicles. Keller and Rice (2010) proposed that human operators display system-wide trust to develop trust towards multiple automated aids at varying levels of reliability. In the context of AAM, vehicles may operate independently from others, while following the generic flight rules set by a governing organization such as the FAA, at varying levels of reliability and automation depending on the situation. Thus, further research is necessary to examine whether SWT theory holds when monitoring multiple vehicles that vary in levels of automation.

Second, empirical investigation is necessary to understand the relationship between human-autonomy trust and attention allocation in AAM environments. In the AAM domain, the attentional demand can fluctuate depending on the number of automated vehicles to monitor and the level of automation in dynamically varying situations for prolonged periods of time. Third, further investigation is necessary to identify other potential factors across the three global factors – individual, situational, and organizational factors – that modulate the relationship between human-autonomy trust and attention allocation. The proposed model does not provide an exhaustive list of factors that influence attention allocation and HAT. However, based on the literature from human-automation interaction, there exist several potential factors that could influence attention allocation and trust in HAT including task load (Karpinsky et al., 2018; Sato

et al., 2020; Sato et al., 2023; Sato & Yamani, 2023), perceived risk (Chancey et al., 2017; Hoesterey & Onnasch, 2023; Sato et al., 2020), and task priority (Sato et al., 2023c). With the framework that the current model offers, further analysis is necessary to examine the human operator's attention allocation strategy and human-autonomy trust in human-AAM technology environments.

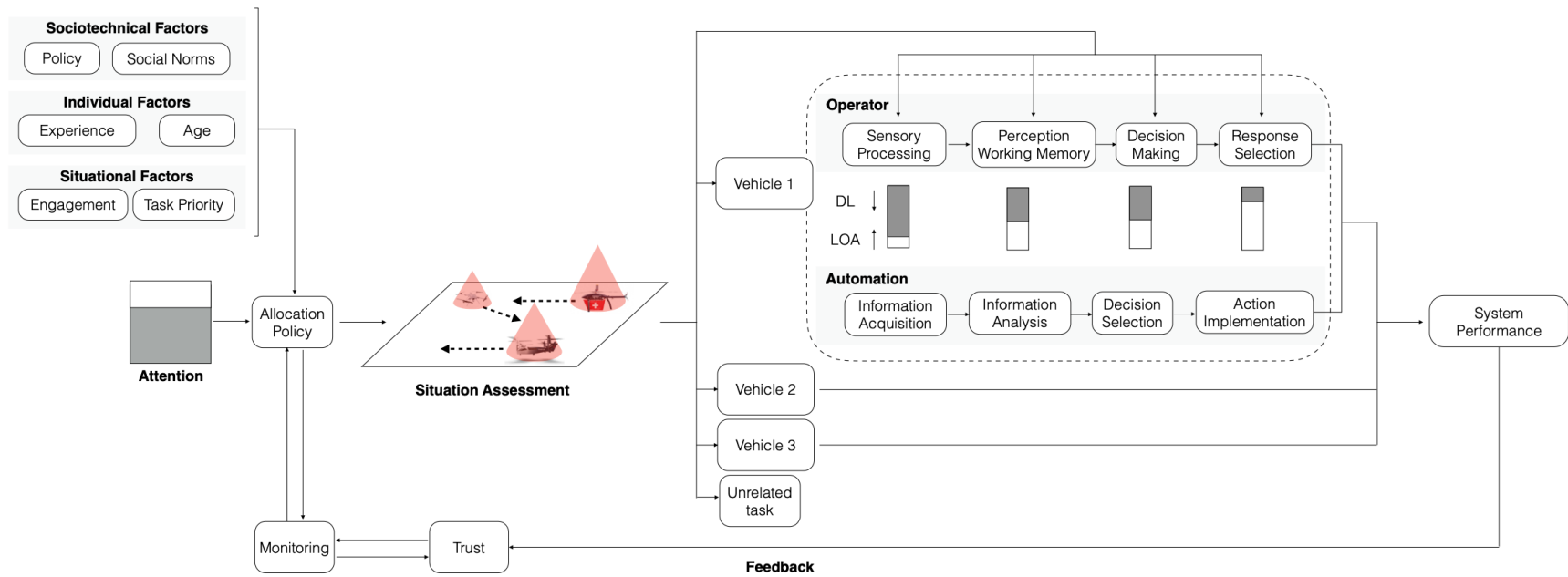


Figure 12.4. An overview of the model of human-AAM interaction focusing on human information-processing capacity limits, levels of automation, and attentional resource allocation.

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