

2023

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Holley, S. J., & Miller, M. D. (2023). Cognitive Processing Disruptions Affecting Flight Deck Performance: Implications for Cognitive Resilience. *Special Issue: Proceedings of the 67th HFES International Annual Meeting*, (). <https://doi.org/10.1177/21695067231196251>

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COGNITIVE PROCESSING DISRUPTIONS AFFECTING FLIGHT DECK PERFORMANCE: IMPLICATIONS FOR COGNITIVE RESILIENCE

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The flight deck of a commercial aircraft has become progressively digitized and operates in multiple modes with displays and indicators that require increasing levels of comprehension. Examining several aspects of cognitive processing is important to understand how threats to safety might occur and what actions might be taken to reduce severity or to eliminate the threat altogether. This paper presents the elements of cognition to consider, relevant characteristics of working memory and cognitive processing speed, types of disruptions and how they are addressed, results from overload or confusion, and the need for effective cognitive resilience to recover and repair the threat. Data from Aviation Safety Reporting System (ASRS) databases indicate 30% of cases could represent a distinct threat of cognitive overload. These are evaluated to identify sources and likelihood for surprise disruptions and to assess the potential of cognitive resilience. Adaptation of the CRM-TEM model is considered for potential application in training and investigations.

OVERVIEW

As commercial flight decks have progressively incorporated digital devices and systems there has been a corresponding increase in mode confusion, unexplained flight control deviations, conflicting systems data, and other challenges to effective cognitive processing of operators. Validating system functions and determining corrective actions becomes more effortful and problematic with disruptions on the flight deck. Typical disruptions may include crew conversations, warnings and alerts, unexpected information, communications with air traffic control or company operations, equipment malfunctions, weather, and many other sources. Usually, operators can address the situations competently using their experience, training, and available resources as effective lines of defense. Occasionally, though, these disruptions may occur in more subtle or insidious ways. They may even manifest as surprises. It is these latter events which are the focus of this paper since they invite significant potential overload of cognitive resources.

COGNITIVE FLOW, LOADING, AND PROCESSING

The primary areas of cognition involved with digital flight decks are flow, load, and processing (Miller & Holley, 2022). Cognitive flow occurs when the skill level and challenge are equal. Among the eight traits associated with flow, those which are key include complete concentration, rewarding experience, effortlessness and ease, and feeling in control. This translates on the flight deck to an optimal level of performance. Distractions and interrupted concentration will disrupt cognitive flow. This, in turn, increases cognitive loading which can override other cognitive functions during times of stress or threat. There is a desirable threshold for optimal processing which, when unanticipated events intercede, can place maximum demand on neural capacities. When exceeded, working memory will prioritize activities to the detriment of some elements cycling in prospective

memory or awaiting recall from long-term memory (Csikszentmihalyi et al., 2014).

Pilot performance decrements may, at times, be attributed to an inadequate interface with the digitized cockpit environment, although this has at other times been explained as mental resource depletion. Coupled with retaining large amounts of information in working memory while processing incoming new information or responding to added secondary tasks will complicate workload effects notably. In a review of studies regarding neurophysiological measurements in pilots while performing flying tasks, Borghini et al. (2014) related connections among mental workload, mental fatigue, and situational awareness. Of significant interest was the finding that high mental workload was accompanied by increased theta and decreased alpha band powers which result in onset of accelerated mental fatigue. These phenomena would likely occur in the medial prefrontal cerebral regions and anterior cingulate cortex.

An area of current debate centers on processing speed of the human brain for cognitive tasks. Processing speed has been described as time taken to perform a cognitive task and has been suggested as a valid measure of mental capacity. Some researchers propose that brain processing speed is limited by the organization of the white matter network along axonal routes connecting brain regions. Other researchers suggest a different view that includes complex arrangements of interconnected networks (Lynn & Bassett, 2019).

Typically, the metrics for task workload do not parallel those for cognitive load. Generalized concepts, as compared with domain-specific knowledge, influence cognitive load differently. For domain specific information, the human brain has a processing capacity between 2 to 60 bits per second (bps) used for attention and decision-making, including perceptual and language processing. Comparatively, the auditory processing rate is about 10,000 bps. For sensory processing, the rate is as high as 106 bps (Fan, 2014). It is

important to consider that conscious cognitive processing involves higher order information and is influenced by the limitations of working memory. The conscious brain can process about 130 messages per second. There are about 86 billion neurons sending 5 to 50 messages per second and the brain has a capacity to process these at around 40 to 50 bps. In an earlier effort to quantify the capacity of cognitive control, researchers manipulated the rate of information flow and determined for higher-level functions a relatively low processing rate of 3 to 4 bps for a given channel. When the rate exceeds capacity, error probability rates increase and performance degrades (Wu et al., 2016).

Previous findings have indicated that cognitive processing speed and working memory are connected. White matter in the brain has been associated with functional activity in structures of the lateral prefrontal cortex and parietal cortex. In research to investigate the effects of training for increasing cognitive processing speed, Takeuchi et al. (2011) confirmed that training-induced plasticity revealed in the left superior temporal gyrus was associated with speeded cognitive processes. They conclude that particular information is domain specific and more work is needed to determine brain regions involved with processing speed. In a feedforward process explaining how working memory may operate, Bouchacourt and Buschman (2019) found neural connections in working memory resulted in inhibitory responses as cognitive loading increased. Their model provides for two interacting networks – one sensory and the other random and capable of learning. The conclusion was that memory capacity is diminished due to interference in the shared network and saturation to the capacity limit.

Functional interaction between the right dorsolateral prefrontal cortex and right superior parietal lobe when working memory engages at higher processing speeds has been associated with intelligence and for resolving complex cognitive processes. An effort to advance understanding of attention and salience network functions that promote cognitive processing showed that working memory is sensitive to task loading that increases response time (Eryilmaz et al., 2020). The between-network coupling among frontotemporal, ventral attention, and default mode networks, and within-network connectivity in the ventral attention network most closely explained differences in low versus high working memory load. The most predictive increases to load response times were within-network connectivity. As a result, when confronted with a task that is cognitively not aligned with the network, a more notable decrease is observed. This effect then diminishes the cognitive processing capacity for the operator and depletes neural resources more rapidly which reduces time available to resolve the disruption.

There is continuing interest in assessing pilot and controller mental workload and growing evidence indicating that increased loading may contribute to performance deficit, control error, compromised safety and pronounced risk among aviation operators. The risk is further exacerbated during

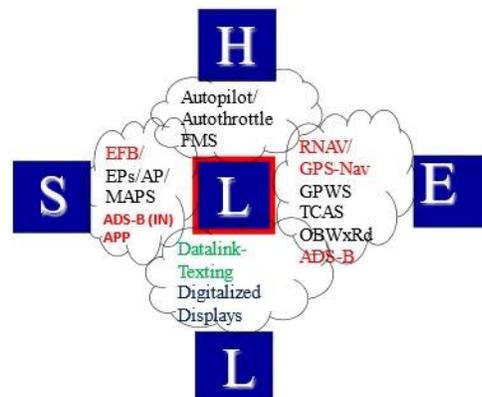
unanticipated situations. Belkhiria and Peysakhovich (2021) found significant relationships between increasing workload and disturbed visual information interpretation. An elevated theta/alpha ratio during high task events was shown to be indicative of an increased cognitive load and a potential for decreased effectiveness of the attentional system.

OVERLOAD AND PERFORMANCE DECREMENT

As described, overreliance on computer-generated information and systems automation has resulted in declining proficiency among commercial pilots in areas of basic flight skills and managing automated systems. Similar instances related to increased digital information and automation have resulted in cognitive overload and compromised situational awareness. Figure 1 illustrates the SHELL model with overlaying cognitive clouds that invite distraction and impinge on processing effectiveness. The risk of overload is a threat.

Figure 1

SHELL With Cognitive Clouds



Note: Adapted from “SHELL Revisited: Cognitive Loading and Effects of Digitized Flight Deck Automation,” by M. Miller and S. Holley, 2018, in C. Baldwin (Ed.) *Advances in Neuroergonomics and Cognitive Engineering*, pp. 95-107 (https://doi.org/10.1007/978-3-319-60642-1_9). Copyright 2018 by Springer International. Reprinted with permission.

The SHELL components (hardware-H, software-S, environment-E, and liveware-L) are discrete domains with functions that interact. The cognitive clouds overlap and form continuous cognitive processing relationships demanding attention and comprehension from the pilots, increasing load.

COGNITIVE THREATS AND DISRUPTIONS

As indicated earlier, an unanticipated or unexplained event can precipitate a disruption to the cognitive flow and processing and contribute an added load. One particular instance is known as automation surprise when crews are not aware of flight system status or which contradicts a shared mental model among operators (Woods & Sarter, 2000).

These may be the result of undetected malfunctions or faulty operator inputs. Human Factors Analysis and Classification System (HFACS) data from the Aviation Safety and Reporting System (ASRS) for 257 landing incidents involving seven different aircraft manufacturers and eleven types of incident revealed the highest frequency of decision errors was associated with inappropriate procedures and knowledge of systems (49.4% at Level 1) and failing to prioritize attention (47.5% at Level 2). Shortcomings in resource management were found in 60.7% of the incidents (Li et al., 2014). This may illustrate deficiencies in cognitive processing speed or overload as precursors of decision errors.

An example on the digitized flight deck illustrating the threat of overtaxed cognitive loading relates to how much information a pilot can cycle actively in working memory before the neural capacity or available resources are overwhelmed. Two recent examples of this occurred with the Boeing 737 Max 8 fatal events in Indonesia (2018) and Ethiopia (2019). These cases illustrate problems when automation surprise occurs. The Boeing 737 MAX 8 has two Angle of Attack vanes but data is taken only from one. By removing some elements of choice from the flight crew, and lacking the training or experience with the newer system, the pilots were not able to understand the problem and why their responses were not effective (NTSB, 2019). For pilots who have known and trusted automation since their earliest flight training, resolving discrepancies and unanticipated flight management system anomalies is less ingrained. Kwak et al. (2018) analyzed 94 cockpit automation accident cases where degraded pilot abilities attributed to heavy reliance on automation and error from increased cognitive workload. This could indicate possibilities for improved cognitive resilience.

Cognitive disruptions, as noted, take the form of interruptions, emergencies, distractions, and similar sources. The authors evaluated ASRS data in four categories (Table 1)

Table 1

ASRS Data Indicating Potential Cognitive Disruption

Report Set Categories and Subcategories	<i>n</i>
Pilot/Controller Communications	
Conflicted Warning	4
Missing Alert	3
Crew Resource Management	
Automation Mismanagement	3
Systems Mismanagement	1
Air Traffic Control	
Loss of Radar/Communications	2
Incorrect Data Assigned	1
Global Positioning System	
Jamming (near military areas)	6
Jamming (foreign airspace)	2
Jamming (all other)	18
Interference	4
Loss of Signal	9

Incorrect Information	7
ADS-B Problem	2
Total	61

Note: Data extracted from four March 2022 NASA ASRS Database Report Sets (n=50 each). <https://asrs.arc.nasa.gov> using a thematic analysis to identify the potential for surprise or unexplained discrepancies in readings or indicators. For each category, the database report set (n=50) was examined to identify where specific mention was made of confusion, information that could not be reconciled or was contradictory to expectations or secondary source information, and which resulted in delayed action or inability to decide on a course of action. Typically, aircrew are trained or experienced in how to identify and resolve these occurrences. At times, though, they may be surprised or confused about what is happening. This further depletes cognitive resources, as described earlier regarding cognitive processing speeds, and slows understanding for how to resolve the discrepancies or anomalies. Taken together, and representing over 30% of all reports for the combined sets, the 61 events identified would suggest a discernable possibility for cognitive overload and subsequent performance decrement. The GPS category, with 94% reporting confusion or unexplained conflicts, is particularly alarming. Aviation is not alone in facing disruption from unknown threats to digital communication systems which can manifest as cyber-attacks, interference or jamming, and systems shutdowns. The incidence of successful cyber-attacks, and accompanying cognitive disruptions, on maritime shipping navigation systems increased 400% globally during 2020 for ships entering port, and 900% from 2017 to 2019 (Maritime Executive, 2020), which should garner attention among aviation authorities.

With Air France Flight 447, when the discrepancies from different pitot probes occurred the autopilot disengaged and shifted to alternate law programming and pilots were confused, incorrectly pulling back on the stick and accelerating the stall. Similarly, when Colgan Air Flight 3407 encountered icing the stall warning system activated but the confused pilot pulled back on the stick rather than lower it to recover. Investigation findings revealed that in both cases the training was deficient in focusing on cognitive resilience. The Royal Aeronautical Society commented that for flight crew encountering unfamiliar situations involving loss of automation the standard training did not provide pilots with the resilience required for automation challenges. There is some hope that the gap may be partially alleviated with expansion of the Multi-Crew Pilot License, an airline-specific alternative introduced by ICAO in 2006 (Flying Vet, 2021).

COGNITIVE RESILIENCE

The literature is replete with descriptions and treatment approaches for cognitive deficits and pathology related to conditions like Alzheimer’s Disease. Other depictions relate to neural plasticity to compensate for disease or trauma as a component of healing (Boros et al., 2017). Cognitive

resilience has experienced a growing interest in the literature including processes associated with age-related cognitive decline, developmental neuropsychology, academic and athletic demands, and cognitive functioning among military personnel. Cognitive resilience is described for organizations, stroke, learning disabilities, mindfulness training, and operating systems. Cognitive resilience is the ability to overcome negative effects or stress on cognitive functioning. One might say that cognitive resilience is derived from neural capacity for refraction, which might be only seconds to achieve stability via the thalamus and basal ganglia (Forsberg et al., 2020). This is more the case on the flight deck.

Often, when stress levels increase there is a decrease in cognitive performance. This may be overcome with prior experience and training to address elevated levels of stress and uncertainty. Some adaptive methods to enhance cognitive resilience have included mindfulness interventions and virtual reality technology (Binsch et al., 2021). Beyond the response actions learned in pilot training, located in checklists, or recalled from manuals, when these are not successful there can be a loss of what actions to take next. During this refractive period, operators may resort to guesses, actions related to functions not involved in the current phenomenon, or calls for assistance. Crew Resource Management (CRM) may be invoked if not already employed. Herein lies the opportunity for cognitive resilience which can preserve neural resources, reduce the cognitive loading, and restore more effective cognitive processes.

In their investigation of resilience in the face of adversity, Parsons, Kruijt, and Fox (2016) proposed an overarching cognitive mapping process as a key component serving to integrate information from several sources. Regarding cognitive resilience, the contributing causation typically is a perceived discrepancy between the situation an operator may be confronted with and their desired conception of reality. The model for cognitive resilience suggests that resolution of conflicts might best be accomplished when not under conscious control. The authors acknowledge that this approach is early in its evolution and research related to situational feedback is not fully understood.

There is, naturally, a need to consider how an individual appraises a situation and whether it generates a stress response. In part, these conditions may be influenced by executive functions and control regarding top-down mental processes of the pre-frontal cortex involving inhibitory control, working memory, and cognitive flexibility. Eysenck et al. (2007) described the resulting cognitive storm that emerges, with increasing automatic biases oriented to the more difficult aspects, ignoring some of the more positive aspects, and selective impairment of executive functions.

At the beginning of this century, the concept of Threat and Error Management (TEM) was added to the (CRM) model used in global efforts to reduce error (European Aviation Safety Agency, 2017). Figure 2 shows one of the models that

illustrate the evaluation and response levels and resolutions for an incident. Cognitive resilience would begin at the threat level where identification and preparation are valuable. The aspects of cognitive processing speed, avoiding overload, and more effective memory retrieval for resources with which to address the threat would prove beneficial. Where crew action or inaction (error) has reduced safety margins, resilience affords the capacity for repair and recovery.

Figure 2

CRM/TEM Model for Cognitive Resilience



Adapted from U.S. Navy (2015) Case study title – Naval Safety Command. <https://navalsafetycommand>

Cognitive resilience can be related to stress and the capacity to effectively cope and resolve the effects. While there are numerous suggestions for building cognitive resilience, these mostly relate to neurogenerative disease or traumatic brain injury losses. The lifestyle and other remedies are not practical for flight deck personnel with specific regard to disruptions. The opportunity exists for further research to determine effective and lasting approaches to building cognitive resilience capacities for pilots. As mentioned, training in increased cognitive processing speeds may be a welcome beginning, as would more targeted expansion of immediate implementation for stress reduction practices that crew members could exercise.

REFERENCES

- Belkhiria, C., & Peysakhovich, V. (2021). EOG metrics for cognitive workload detection. *Procedia Computer Science*, 192, 1875-1884. <https://doi.org/10.1016/j.procs.2021.08.193>
- Binsch, O., Bottenheft, C., Landman, A., Roijendijk, I., & Vermetten, E. H. (2021). Testing the applicability of a virtual reality simulation platform for stress training of first responders. *Military Psychology*, 33, 182-196. doi: 10.1080/08995605.2021.1897494
- Borghini G., Astolfi L., Vecchiato G., Mattia D., & Babiloni F. (2014). Measuring neurophysiological signals in aircraft pilots and car drivers for the assessment of mental workload, fatigue and drowsiness. *Neuroscience & Biobehavioral Reviews*, 44, 58-75

- Boros, B. D., Greathouse, K. M., Kelsey, M., Gentry, E. G., Curtis, K. A., Birchall, E. L., Gearing, M., & Herskowitz, J. H. (2017). Dendritic spines provide cognitive resilience against Alzheimer's disease. *Annals of Neurology*, 82(4), 602-614.
<https://doi.org/10.1002/ana.25049>
- Bouchacourt, F., & Buschman, T. (2019). A flexible model of working memory. *Neuron*, 103, 147-160.
<https://doi.org/10.1016/j.neuron.2019.04.020>
- Csikszentmihalyi, M., Abuhamdeh, S., & Nakamura, J. (2014). *Flow and the foundations of positive psychology*. Springer Publishing.
- European Aviation Safety Agency. (2017). *CRM training* [online]. <https://www.easa.europa.eu/en/document-library/general-publications/crm-training-implementation/>
- Eryilmaz, H., Dowling, K., Hughes, D., Rodroques-Thompson, A., Tanner, A., Huntington, C., Goon, W., & Roffman, J. (2020). Working memory load-dependent changes in cortical network connectivity estimated by machine learning. *Neuroimage*, 271, 116895.
<https://doi.org/10.1016/j.neuroimage.2020.116895>
- Eysenck, M. W., Derakshan, N., Santos, R., & Calvo, M. G. (2007). Anxiety and cognitive performance: attentional control theory. *Emotion*, 7(2), 336-353.
<http://dx.doi.org/10.1037/1528-3542.7.2.336>
- Fan, J. (2014). An information theory account of cognitive control. *Frontiers in Human Neuroscience*, 8, 680.
<https://doi.org/10.3389/fnhum.2014.00680>
- Forsberg, H., Linden, J., Hjorth, J., Manefjord, T., & Daneshmand, M. (2020). Challenges in using neural networks in safety-critical applications. *2020 AIAA/IEEE 39th Digital Avionics Systems Conference (DASC)*, 1-7.
<https://doi.org/10.1109/DASC50938.2020.9256519>
- FlyingVet. (2021, Jan 9). Automation in aircraft: The changing role of the pilot. *TurboFuture*.
<https://turbofuture.com/search?query=automation+in+air+cra%3A+the+changing+role+of+the+pilot>
- Kwak, Y., Choi, Y., & Choi, J. (2018). Analysis between aircraft cockpit automation and human error related accident cases. *International Journal of Control and Automation*, 11(3), 179-192.
<http://dx.doi.org/10.14257/ijca.2018.11.3.16>
- Li, W., Kearney, P., Braithwaite, G., & Lin, J. (2018). How much is too much on monitoring tasks? Visual scan patterns of single air traffic controller performing multiple remote tower operations. *International Journal of Industrial Ergonomics*, 67, 135-144.
<https://doi.org/10.1016/j.ergon.2018.05.005>
- Lynn, C., & Bassett, D. (2019) The physics of brain network structure, function and control. *National Review of Physics*, 1, 318-332. <https://doi.org/10.1038/s42254-019-0040-8>
- Maritime Executive. (2020). *Report: Maritime cyberattacks up by 400 Percent* [online], (29 June 2020). <https://maritime-executive.com/article/report-maritime-cyberattacks-up-by-400-percent> (accessed 29 January 2023).
- Miller, M., & Holley, S. (2022). Assessing human factors and cyber attacks at the human-machine interface: Threats to safety and pilot and controller performance. In T. Ahram & W. Karwowski (Eds.), *Human Factors in Cybersecurity*, 53, 74-83. AHFE Open Access.
doi.org/10.54941/ahfe1002204
- Miller, M. & Holley, S. (2018). SHELL revisited: Cognitive loading and effects of digitized flight deck automation, in C. Baldwin (Ed.), *Advances in Neuroergonomics and Cognitive Engineering*, pp. 95-107.
https://doi.org/10.1007/978-3-319-60642-1_9
- National Aeronautics and Space Administration. (2022). *ASRS Database Report Sets* [online]. Available at: <https://asrs.arc.nasa.gov>.
- National Transportation Safety Board. (2019). Assumptions used in the safety assessment process and the effects of multiple alerts and indications on pilot performance, safety recommendation report, *NTSB-ASR-19-01*, 2019, pp. 1-13. <https://www.ntsb.gov/investigations/accidentreports/reports/asr1901.pdf>.
- Parsons, S., Kruijt, A-W., & Fox, E. (2016). A cognitive model of psychological resilience. *Journal of Experimental Psychopathology*, 3, 296-310.
doi:10.5127/jep.053415
- Takeuchi, H., Taki, Y., Hashizume, H., Sassa, Y., Nagase, T., Nouchi, R., & Kawashima, R. (2011). Effects of training on processing speed on neural systems. *Journal of Neuroscience*, 31(34), 12139-12148
doi:10.1523/JNEUROSCI.2948-11.2011
- U.S. Dept. of Navy. (2015). Case study title – Naval Safety Command. [Powerpoint presentation]. [https://navalsafetycommand.navy.mil/Portals/29/Documents/AS%20TEMP-TEM%20\(comp\).pptx?ver=gJ9AOnLenHrG1kuCxluC5w%3D%3D](https://navalsafetycommand.navy.mil/Portals/29/Documents/AS%20TEMP-TEM%20(comp).pptx?ver=gJ9AOnLenHrG1kuCxluC5w%3D%3D)
- Woods, D., & Sarter, N. (2000). Learning from automation surprises and “going sour” accidents. In N. Sarter & R. Amalberti (Eds.), *Cognitive engineering in the aviation domain*, pp. 327-353. Lawrence Erlbaum Associates.
- Wu, T., Dufford, A., Mackie, M., Egan, L., & Fan, J. (2016). The capacity of cognitive control estimated from a perceptual decision making task. *Scientific Reports*, 6, 34025. <https://doi.org/10.1038/srep34025>