

## Human Factors and Neuroscience in Next-Generation Simulation Environments

<b>LCDR N.J. Armendariz, PhD</b>	<b>J.J. Walcutt, PhD</b>	<b>Christina Parker, EdD</b>	<b>LT Brittany Neilson, PhD</b>
<b>US Navy School of Aviation</b>	<b>DAF A1D</b>	<b>AFSOC</b>	<b>NAWCAD</b>
<b>Pensacola, FL</b>	<b>Alexandria, VA</b>	<b>Hurlburt Field, FL</b>	<b>Patuxent River, MD</b>
<b>Nicholas.j.armendariz.mil@us.navy.mil</b>	<b>Jennifer.walcutt.1@us.af.mil</b>	<b>Christina.parker.9@us.af.mil</b>	<b>Brittany.n.neilson.mil@us.navy.mil</b>

### ABSTRACT

This paper introduces a framework designed to enhance training effectiveness by creating next-generation simulation environments that replicate complex operational tasks. Central to the framework is the collection and integration of neurophysiological and behavioral data to assess how immersion and realism influence learning outcomes. The approach systematically utilizes neurophysiological signals—such as cortical activity, autonomic nervous system activity, and eye tracking—in combination with real-time cognitive monitoring and behavioral evaluations to generate comprehensive individual performance profiles that can be leveraged to design adaptive training. Specifically, real-time, precise adjustments to training can be tailored to each individual's needs, whether that be adjusting the difficulty or providing feedback in real time.

Initial experiments have demonstrated the framework's capability to accurately forecast performance outcomes, offering actionable insights for recruitment and personalized training design. However, testing has primarily been conducted in controlled settings with a general population and limited selection of neurophysiological metrics. Given substantial improvements in reliability of neurophysiological monitoring tools since their earlier usage in programs like the Defense Advanced Research Projects Agency (DARPA) Augmented Cognition program (St. John et al., 2004), revisiting and refining this integrated approach is now feasible and essential. The proposed framework identifies specific areas requiring improvement, supports real-time neurophysiological adjustments, and optimizes individual trainee performance. By aligning training methods with operational needs, the framework enhances efficiency and resource allocation, directly supporting the Department of Defense's objectives for increased readiness and operational lethality.

### ABOUT THE AUTHORS

**LCDR N. J. "Terror" Armendariz, PhD**, is an instructor at the Naval School of Aviation Safety, where he teaches Human Factors and Fixed-Wing Aerodynamics. He served as a Marine Electronic Countermeasures Officer in the EA-6B for 12 years prior to service under OSD Personnel and Readiness, before becoming a Navy Aerospace Experimental Psychologist.

**J.J. Walcutt, PhD** is a scientist, innovator, and learning engineer that specializes in strategic development and reform across education, military, and government. She is currently serving as a Highly Qualified Expert (HQE) in Human Development for the USAF (HAF/A1D). In this role, she is leading the design of an Air Force Development Strategy and providing advisement across a variety of assessments, strategic, and technology-enabled projects aimed at enhancing human capabilities.

**Christina Parker, EdD** U.S. Air Force, brings 22 years of experience in government service in her role as the Chief Learning Officer at Air Force Special Operations Command, Hurlburt Field AFB. Her career as an Instructional Systems Technologist includes research in education technology and instructional design, with a particular emphasis on the effective integration of technology in military training programs. Her work explores pioneering approaches such as incorporating neurofeedback as a design and as a learning tool. Dr. Parker holds degrees from the University

of South Alabama and a doctorate from Indiana University. She has been sharing her expertise as an adjunct professor for 19 years, most currently with Indiana University.

**LT Brittany Neilson, PhD**, is an Aerospace Experimental Psychologist for the United States Navy. She is presently a Project Officer in the Human Systems Engineering Department at the Naval Air Warfare Center Aircraft Division in the Naval Air Station Patuxent River, MD. She is leading an effort with a multidisciplinary team to develop brain-computer interface capabilities at NAWCAD.

## Human Factors and Neuroscience in Next-Generation Simulation Environments

**LCDR N.J. Armendariz, PhD**  
US Navy School of Aviation  
Pensacola, FL  
Nicholas.j.armendariz.mil@u  
s.navy.mil

**J.J. Walcutt, PhD**  
DAF A1D  
Alexandria, VA  
Jennifer.j.walcutt.civ@us.af.  
mil

**Christina Parker, PhD**  
AFSOC  
Hurlburt Field, FL  
Christina.parker.1@u  
s.af.mil

**LT Brittany Neilson, PhD**  
NAWCAD  
Patuxent River, MD  
Brittany.n.neilson.mil@u  
s.navy.mil

### INTRODUCTION

Military aviation operates at the outer edges of human cognitive and physical performance. It is an unforgiving environment where decisions must be made under pressure, and errors can result in catastrophic outcomes. Despite the demands placed on today's aircrew, much of the training pipeline remains wedded to linear, time-bound instructional models that fail to reflect the real-time demands of combat or crisis scenarios. This discrepancy introduces a critical gap between what is trained and what is required when lives are on the line.

The modern warfighter no longer operates in a predictable, industrial-age battlespace. Today's military missions are conducted in dynamic, information-rich environments that place unprecedented demands on attention, decision-making, and adaptability. Further, the rapid increase in hybrid Fleets that supplement crewed platforms with uncrewed assets is a significant shift in the expectations put on the human. Yet, the learning systems designed to prepare warfighters often treat all learners identically, regardless of their individual cognitive states or physiological readiness. Simulation fidelity may be high, but without meaningful adaptation to the learner's state, the value of even the most realistic training scenarios is diminished.

From the psychologist's view, we understand that cognitive load, emotional regulation, and attentional control are key variables that influence how—and whether—learning occurs. From the cockpit, we see that task saturation, checklist fixation, and tunnel vision are lived experiences that unfold in seconds, not semesters. Additionally, diminished performance from monitoring highly automated systems or complacency in routine tasks can result in hazardous states of awareness (Prinzel, 2002) that can become dangerous quickly given an unexpected event. If training systems are to truly support mission readiness, they must be capable of interpreting these internal states and responding with instructional agility.

This paper introduces a novel framework for real-time, adaptive training. It centers on the concept of Learning Opportunity Zones (LOZs), which we are defining as distinct moments when a learner's internal state suggests either a struggle, disengagement, or cognitive opening. Said another way, these are inflection points where performance is at risk and training value is the highest. So, the LOZs are *both* opportunities and vulnerabilities in the learning process, and points to why detecting them in real-time matters. By capturing and responding to these moments using neurophysiological and behavioral data, the system transitions from static instruction to a live feedback loop tailored to optimize performance. This approach is especially timely as military education doctrine, including the shift toward Outcomes-Based Military Education (OBME), increasingly prioritizes learner-centric design and measurable proficiency over compliance-driven timelines.

### BACKGROUND AND RELATED WORK

The need for real-time, adaptive training systems is not new. What is new is the convergence of technological, neuroscientific, and instructional capabilities that make such systems viable in operational contexts. This framework draws heavily from three foundational streams of research: Neurophysiological state monitoring, adaptive learning design, and military education policy.

## Neurophysiological State Monitoring

Efforts dating back to the Defense Advanced Research Projects Agency (DARPA) Augmented Cognition (AugCog) program (St. John et al., 2004) demonstrated the feasibility of interpreting cognitive load using real-time, neurophysiological signals. The program focused on a wide range of non-invasive technologies, including electroencephalography (EEG), event-related potentials (ERP), functional near-infrared spectroscopy (fNIRS), galvanic skin response (GSR), heart rate variability (HRV), pupil dilation, and various head and body movements, to define cognitive state information that was measured by “gauges” (i.e., computations derived from neurophysiological indicators) in applied settings. The extensive, integrated suite of gauges was one of the more impressive aspects of the program, but interestingly, there were differences in gauge sensitivity across cognitive tasks and even across individuals (St. John et al., 2004). While these efforts demonstrated that internal states could be inferred in real time and linked to workload thresholds, enabling a vision of adaptive interfaces and decision support systems for warfighters operating under duress (ONR, 2006), continued work is needed to better characterize cognitive states and account for interindividual differences.

Based on this early work, the state-based information-loss processing (Vogel-Walcutt, Carper, Bowers, & Nicholson, 2010) model was developed to emphasize what these neurophysiological markers can indicate during learning. The SIP model is a cognitive framework derived from foundational memory theory that maps how information can be lost at various stages of learning, particularly when acquiring and applying higher-order knowledge. It tracks the flow of information from sensory memory through short-term memory (STM) into long-term memory (LTM) and finally to output, identifying critical points where information may be forgotten, misinterpreted, misfiled, or lost due to internal learner states like inattention or disinterest. Key vulnerabilities include unattended sensory input, STM limitations (e.g., task shedding, forgetting), and errors in filtering, comprehension, or labeling, which can hinder LTM encoding. Even if information reaches LTM, it must be properly retrieved and transformed into applicable knowledge; otherwise, it remains inert and unusable. The model emphasizes that without strategic instructional interventions, such as scaffolding, metacognitive prompts, and adaptive feedback, learners may fail to convert stored information into meaningful, real-world performance (Vogel-Walcutt, Carper, Bowers, & Nicholson, 2010). In order to facilitate a state-based SIP model, continued work is needed to accurately classify states of cognitive breakdown and to effectively design instructional interventions, both of which need to be feasible for operational simulation environments. However, advancements in algorithm development and neurophysiological indicators of learning support the potential for such an adaptive learning model.

## Adaptive Learning Design

**Algorithms Physiologically Derived to Support Learning Efficiency.** Adaptive Learning Design and models are based on measurements of neurophysiological states and can implement changes into the learning plan as needed, when needed. These strategies form frameworks for selecting optimal instructional strategies tailored by knowledge type, learner expertise, group size, and training environment. Strategies were organized across pre-, during-, and post-training phases, mapped to Gagne’s nine instructional events and rated for effectiveness. These include methods like mindfulness, scaffolding, intelligent tutoring systems, and concept mapping—aimed at improving declarative, procedural, and higher-order cognitive skills acquisition (Vogel-Walcutt, Fiorella, & Malone 2013).

**Neurophysiological Indicators of Learning.** Following a hiatus in this work, neurophysiological technologies were enhanced beyond the laboratory to become more ruggedized, stable, and valid. New studies integrated these real-time neurophysiological data—particularly EEG-based cognitive load (CL) measurements—into military training systems to personalize instruction, optimize learning efficiency, and accelerate skill acquisition. Findings suggest that traditional, time-intensive models of training are no longer viable in high-tempo, technologically saturated battlespaces. Instead, adaptive, neurophysiologically-informed systems can dynamically adjust training content based on each learner’s cognitive state, preventing under- and over-load. One specific study explored EEG-based classifiers across three cognitive tasks, showing promising accuracy even with reduced electrode sets, indicating feasibility for portable and cost-effective deployment (Walcutt et al., 2020). Findings highlighted that EEG-based CL data, when individualized and task-specific, can power neurophysiologically-adaptive training platforms that preserve human capital, reduce attrition, and enhance warfighter readiness.

Recent advancements have taken this further. Parker et al. (2023) mapped EEG patterns in Army aviation environments and demonstrated that neural signatures—particularly theta/alpha and beta band activity—can

distinguish between moments of active learning and mastery. Similarly, Balconi and Crivelli (2020) highlight how changes in heart rate variability (HRV) and galvanic skin response (GSR) can be used to detect stress reactivity, cognitive fatigue, and recovery potential. Together, these findings suggest that moment-to-moment fluctuations in the body can be harnessed to make training more responsive, precise, and personalized.

Parker et al. (2025) built on these insights with a related study indicating the feasibility of integrating EEG monitoring into virtual reality-based training environments for Air Force Special Operations maintainers. Initial results suggests that while data quality varied based on participant experience, discernible neural patterns emerged that correlated with expected cognitive load levels, particularly for participants with stronger data collection. These patterns, while susceptible to motion artifacts, suggest that real-time cognitive load decoders could mitigate noise and inform instructional adjustments. In alignment with established research, observed increases in theta and beta activity during task performance further support the potential to utilize EEG data to identify moments of cognitive disengagement and to tailor training interventions for optimized learning outcomes in high pressure operational scenarios.

### Military Education Policy

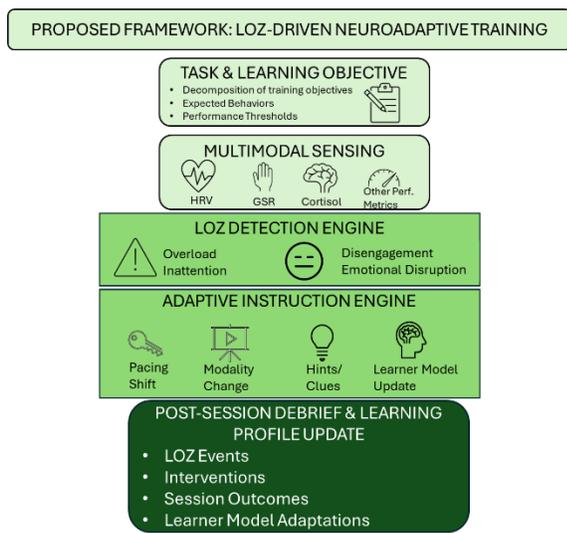
**Instructional Systems Design and Military Alignment.** Parallel developments in military instructional systems, including the IMITATE program and Walcutt’s adaptive learning models, emphasize the importance of feedback, learner modeling, and scenario agility. These systems have successfully demonstrated how instructors can improve their delivery based on real-time performance cues. Our framework extends this logic to the physiological domain, allowing training systems to adjust content and pacing based not just on errors, but on the signals that precede them.

**Policy Shifts and Strategic Opportunity.** The Department of Defense’s adoption of Outcomes-Based Military Education (OBME) principles reflects a larger shift away from hours-based training to a focus on competency, mission alignment, and evidence of learning (Mulready-Stone, 2024). This shift requires not only better assessments, but better instruction—systems that can detect when a learner is ready to move forward, when they need remediation, or when emotional or cognitive factors are impeding progress. The LOZ-based framework proposed here is designed precisely to meet that need.

As sensing technologies become lighter, cheaper, and more robust—and as our models of cognition grow more precise—the opportunity to close the readiness gap through real-time learning optimization has never been greater. The time is right to fuse the cockpit and the classroom, bringing together the best of neurophysiology and operational instruction to build training systems worthy of today’s mission demands.

### PROPOSED FRAMEWORK OVERVIEW

The proposed neuroadaptive training framework is anchored in the principle that learning is dynamic, nonlinear, and physiologically embedded. It moves beyond rote measurement of outcomes and into the realm of real-time learning interpretation. At its center is the identification of Learning Opportunity Zones (LOZs)—defined as the neurobehavioral “inflection points” where the probability of learning gain is highest, but equally at risk of being lost without instructional support. In this sense, LOZs represent both opportunities to accelerate performance and vulnerabilities where training value may collapse without timely intervention.



of outcomes and into the realm of real-time learning interpretation. At its center is the identification of Learning Opportunity Zones (LOZs)—defined as the neurobehavioral “inflection points” where the probability of learning gain is highest, but equally at risk of being lost without instructional support. In this sense, LOZs represent both opportunities to accelerate performance and vulnerabilities where training value may collapse without timely intervention.

The framework functions through four integrated modules: task analysis, multimodal sensing, LOZ classification, and adaptive instructional response. The process begins with breaking down operational tasks into discrete, measurable components. These components are then mapped to expected ranges of cognitive load and attentional demand using validated benchmarks (Walcutt & Schatz, 2018). Physiological signals—HRV, GSR, eye-tracking, and EEG—are gathered through non-invasive sensors and continuously compared to a trainee’s historical and baseline data. A fusion engine synthesizes these streams to

Figure 1. Learning Opportunity Zone Flow

determine when a learner enters a LOZ. LOZs are categorized into four types (see Table 1), though it is important to recognize that categories may overlap and accurate classification generally requires integration of multiple indicators rather than reliance on any single metric.

Equally critical is the recognition that LOZs are inherently personalized. Generalizable thresholds across all learners are unlikely; instead, LOZ markers must often be tailored to the individual, their task, and their operational environment. This personalization ensures that what signals overload or disengagement for one trainee is not misinterpreted for another.

Once classified, LOZs trigger an adaptive engine that selects the most appropriate instructional intervention: pacing adjustments, scaffolded feedback, scenario branching, or cognitive recovery prompts. Each intervention is tracked, and its effect on performance and physiology is used to refine future decisions. These adaptations can be automated, instructor-directed, or a hybrid approach, with the instructor retaining authority to override or augment the system’s recommendations. Clarifying this human–machine partnership is central to building trust in neuroadaptive systems.

To illustrate, consider a cockpit training simulation: if EEG and HRV indicators suggest cognitive overload during instrument approach, the system might slow scenario pacing or cue the instructor to deliver targeted feedback. Conversely, if disengagement is detected, the system could increase task complexity or inject anomalies to sustain attention. In this way, the LOZ framework grounds abstract physiological data in operationally meaningful training moments.

Physiological signals—HRV, GSR, eye-tracking, and EEG—are gathered through non-invasive sensors and continuously compared to a trainee’s historical and baseline data. A fusion engine synthesizes these streams to identify when a learner enters a LOZ. LOZs are categorized into four types (see Table 1).

**Table 1. LOZ Categories**

<b>LOZ Type</b>	<b>Indicators</b>	<b>Adaptive Response</b>
<b>Cognitive Overload</b>	High GSR, increased theta EEG, frequent task errors, delayed response times	Slow pacing, inject scaffolds, reduce task complexity
<b>Underload/Disengagement</b>	Low HRV, flat eye-tracking, low error rate + long latency	Increase novelty, introduce challenge, inject anomalies
<b>Frustration/Anxiety Spikes</b>	Fluctuating HRV, gaze scatter, erratic decision patterns	Insert recovery window, reframe objective, emotional cue
<b>Transition to Mastery</b>	Decreasing cognitive load, consistent accuracy, smooth eye-paths	Advance scenario, inject variation, reduce instructor input

These signatures reflect work in cognitive neuroscience (Balconi & Crivelli, 2020) and aviation neuro-mapping (Parker, et al., 2025; Parker, et al., 2023). It is important to note that additional work is needed to validate indicators of LOZ types in mission-specific tasks and environments with individuals unique to the operational context, as generalizable indicators of LOZ types may not be feasible, and instead, indicators of LOZ. types may need to be unique to specific tasks and individuals.

Once classified, LOZs trigger an adaptive engine that selects the best-fit instructional intervention: pacing adjustments, scaffolded feedback, scenario branching, and/or cognitive recovery prompts. Each intervention is tracked, and its effect on performance and physiology is used to refine future decisions.

By embedding this closed-loop learning model, the framework supports OBME by linking learner state to observable outcomes—before errors become entrenched. It shifts the instructor’s role from evaluator to active mission planner in the learner’s development.

**Considerations for Acquisition and Transition**

Despite the promise of neuroadaptive systems, multiple barriers exist within traditional defense acquisition structures that could hinder operational adoption.

### **Category Misalignment**

Neuroadaptive tools often fall between established acquisition categories, lacking clear designation under existing JCIDS or DoD 5000 series programs. These systems are neither purely software nor hardware, complicating milestone justification and requirements generation. Physiological and biometric data, while generally unclassified, are highly sensitive and subject to strict DoDI 5400.11 and RMF processes. Systems that rely on real-time processing or third-party cloud storage may struggle to secure Authority to Operate (ATO) within operational timelines.

### **Testing and Evaluation Gaps**

Traditional DoD acquisition frameworks heavily emphasize Technology Readiness Levels (TRL) as indicators of maturity. However, neuroadaptive training systems introduce unique complexities where system readiness for *human use* is just as critical as technical performance. The Human Readiness Levels (HRL) (See, 2021) offers a nine-level framework for assessing whether technologies are suitable, usable, and operationally safe for their intended human end-users in realistic conditions.

The HRL scale provides a structured pathway parallel to TRLs and shifts the focus from lagging indicators like human error in fielded systems to leading indicators – such as usability, cognitive fit, and operator-system integration. Incorporating these assessments into neuroadaptive system development ensures that not only is the technical system functioning, but that humans can reliably interact with it under load, stress, and op tempo. Applying HRL early in the prototyping phases could prevent late-stage rejection due to friction points that often prevent training interventions.

Programs that allow for reporting of both HRL and TRL at major milestone reviews allow acquisition decision makers to align system maturity with human-centered risk mitigation. For the neuroadaptive tools, seeing a lag in HRL versus TRL may indicate that additional testing is needed, or perhaps a redesign of protocols for the end-user, especially if biometric data or adaptive logic could influence the evaluation of the certification pathways. Integrating HRL evaluation complements RMF, OTAs and Adaptive Acquisition Framework practices and can improve the integration of human-centered tech.

### **Funding Stream Fragmentation**

RDT&E budgets may fund early development, but operational implementation often requires O&M or procurement funds—rarely aligned to accommodate adaptive training systems. This misalignment contributes to the so-called “valley of death” between research and fielding.

### **Cultural Trust and Risk Aversion**

Both acquisition offices and operational leaders are hesitant to integrate systems that alter high-stakes training pipelines without clear guarantees. Neuroadaptive feedback systems, especially those involving biometric data, must address concerns over fairness, transparency, and impact on evaluation.

To address these challenges, acquisition pathways such as the Adaptive Acquisition Framework (AAF) or Software Acquisition Pathway (DoDI 5000.87) may provide the flexibility needed. Other Transaction Authorities (OTAs) may also be explored for rapid experimentation in partnership with research labs and user communities.

Addressing these institutional, procedural, and cultural concerns will be as vital to success as technical maturity. Future research must treat acquisition strategy as a design component—not an afterthought.

### **Validating Learning Opportunity Zones**

While the LOZ framework offers a compelling model for detecting and responding to critical inflection points in learning, its utility ultimately depends on rigorous validation. Several pathways can establish confidence in the accuracy and value of LOZ classifications. In order to do this it is key that the validation be contextual and task-specific (Balconi & Crivelli, 2020).

First, controlled simulation studies should be conducted where LOZ detections are compared against independent measures of workload and performance, such as NASA-TLX ratings, observed error rates, or subjective stress reports. This provides an empirical foundation to confirm whether LOZ signals correspond to meaningful shifts in cognitive or emotional state.

Second, LOZ classification should rely on the convergence of multiple indicators—such as EEG paired with HRV or gaze metrics combined with task performance—rather than a single signal. Requiring corroboration across modalities reduces the risk of false positives and improves robustness in operational settings.

Third, alignment with instructor and subject-matter expert (SME) judgment is critical. By having SMEs annotate “critical learning moments” during training, researchers can compare expert observation with system-detected LOZs, refining thresholds to better match human assessment.

Fourth, validation should occur within specific mission contexts. Aviation emergency procedures, trauma care simulations, and distributed command exercises may each produce different physiological signatures of overload, disengagement, or mastery. Demonstrating that LOZ detection holds—or appropriately adapts—across domains strengthens confidence in its generalizability.

Finally, outcome-based validation is essential. Tracking whether interventions triggered during LOZs lead to measurable improvements in retention, transfer, or operational performance provides the strongest evidence that acting on LOZs enhances readiness. These efforts should be coupled with Human Readiness Level (HRL) evaluations, ensuring not only that the system is technically valid, but also that it is trusted, usable, and ethically sound for learners and instructors.

Importantly, validating LOZs cannot fall to a single organization. Success will require a joint effort between military laboratories, academic researchers, and industry developers to build shared protocols, datasets, and validation benchmarks. Military stakeholders can define operationally relevant use cases, academia can provide methodological rigor and theoretical grounding, and industry can ensure scalable, field-ready implementation.

LOZ validation should be pursued as a consortium priority, uniting military, academic, and industry partners to ensure these tools evolve responsibly into trusted and effective components of future training systems.

## **IMPLEMENTATION AND USE CASE VISION**

The aviation domain presents a uniquely fertile environment for deploying and refining the neuroadaptive training framework. Not only does flight training rely heavily on simulation—providing a controlled and repeatable environment for data collection—but aviation tasks are inherently multimodal, time-sensitive, and cognitively demanding (Wickens et al., 2008). These characteristics make them particularly suitable for real-time neurophysiological monitoring and adaptive instruction (Parker et al., 2023).

At a foundational level, aviation training offers access to embedded performance metrics (e.g., flight path adherence, systems management, checklist compliance) which serve as direct behavioral correlates to cognitive and emotional states. When coupled with real-time physiological sensing, these metrics can reveal where trainees are operating near the edge of their capabilities—what we now define as Learning Opportunity Zones (LOZs).

Consider a scenario in which a rotary-wing trainee exhibits elevated skin conductance levels, coupled with slowed reaction times and erratic gaze patterns while navigating emergency autorotation procedures. Rather than simply logging errors for post-hoc review, the neuroadaptive system intervenes mid-scenario, pausing the simulation, delivering a tailored verbal cue, or replaying a previous decision path to encourage reconsolidation. Such interventions are not only timely—they are calibrated to the learner’s internal state, increasing the likelihood of encoding and retention (Balconi & Crivelli, 2020; Walcutt et al., 2023).

Training environments further offer opportunities to embed EEG-based cognitive load monitoring, particularly in high-tempo tasks such as instrument approaches, formation flying, or abnormal systems management. By establishing individualized baselines during routine flight profiles, the system can more accurately identify divergence during complex sequences, surfacing LOZs in real-time

Beyond aviation, medical and command training domains offer similarly promising use cases. In trauma care simulations, for instance, a drop in attentional focus—as indicated by eye-tracking and heart rate variability—could prompt a short cognitive pause or change in visual stimuli to mitigate task saturation. In distributed command decision-

making exercises, trainees often experience attention collapse during prolonged scenario briefings. EEG-based detection of disengagement, paired with gaze mapping, could trigger re-engagement strategies such as interactive recaps or split-team planning injects.

Importantly, the system is designed with scalability and modularity in mind. Sensor suites can be adjusted based on environmental constraints and training goals, and adaptive interventions are built to align with instructor pacing, scenario branching logic, and existing LMS infrastructure. This modularity ensures the framework can be deployed not only in elite pilot training pipelines, but also across enlisted aviation maintenance, intelligence operations, and tactical command education tracks. Trials documented in Vierling et al. (2018) and findings from the TEM Journal neurofunctional deployment study support the feasibility of this modular integration.

Additionally, the SoLaR Exemplar Report (2020) provides a roadmap for managing the digital learning data ecosystem necessary to scale such a solution across joint and interagency training environments. These insights guide the architecture for both secure data handling and meaningful performance feedback.

Ultimately, by identifying friction points during training—not after errors have occurred but as cognitive strain develops—this framework enables more precise allocation of instructional resources. It supports OBME by directly linking internal state measurements to performance outcomes and enabling just-in-time instructional support, a capability long sought but rarely delivered in military learning ecosystems (Mulready-Stone, 2024; Walcutt & Schatz, 2018).

## **FUTURE WORK AND CONSIDERATIONS**

To move from concept to capability, the next phase involves development of a prototype system, including integration of a modular sensor suite with a data fusion and adaptation engine. Pilot testing in flight simulation environments will assess the reliability of LOZ detection, the efficacy of real-time interventions, and the impact on long-term retention and decision accuracy.

Further exploration will include integration with existing learning management systems and immersive platforms (e.g., XR training suites), as well as governance mechanisms to ensure ethical use of biometric data. Importantly, research into trainee and instructor trust in system-generated interventions will inform adoption strategies. Incorporating user-centered design principles will help ensure that trainees perceive adaptations as supportive rather than corrective—a key concern in maintaining psychological safety and motivation.

In alignment with NATO's HFM-311 recommendations (Dugan & Baloi, 2022), trust-building strategies such as transparent algorithms, instructor override capabilities, and visualization of biometric feedback must be prioritized. This ensures operational users maintain confidence in the system's fidelity and purpose.

The ARL-SR-0333 Effectiveness Evaluation Research Outline provides a valuable blueprint for how future validation studies can be structured to include longitudinal tracking, cross-domain applicability, and dual-performance outcomes (behavioral and physiological). These studies will also explore model-driven insights for tailoring instruction over time based on learner history and known response-to-intervention trends.

To support scaling, future work must also engage in cross-functional collaboration across neurocognitive researchers, simulation engineers, and policy architects to define acquisition pathways for adaptive training platforms. This includes exploration of acquisition reform models to support rapid prototyping and field testing without loss of scientific rigor. The time to act is now—while sensing technology is accessible, doctrine is shifting, and operational demands require training systems that respond in real time to learner state. By translating neuroscience into instruction, and instruction into operational advantage, this framework lays a credible path forward.

## **CONCLUSION**

The Learning Opportunity Zone framework offers a paradigm shift in how we think about training effectiveness. By leveraging real-time insights into the learner's internal state, we can build instructional systems that respond with the same adaptability we expect from our warfighters. This paper outlines a path toward a neuroadaptive ecosystem that connects body, brain, and behavior with mission-aligned learning outcomes.

While grounded in aviation use cases, the framework's potential spans all cognitively intensive military domains. In a future where complexity is constant, readiness must be responsive. This framework is a step toward that reality through the translating of findings into concrete guidelines for instructional systems designers as well as establishing robust verification, validation, and accreditation protocols to ensure effectiveness of the neuroadaptive training systems on learning and performance in highly complex, rapidly evolving battlespaces. At the same time, these advances carry ethical considerations. The potential benefits—greater safety, precision, and learning efficiency—must be weighed against risks of data misuse, privacy concerns, and over-reliance on biometric indicators (Korean Neurological Association, 2020). The responsible path forward is to employ these tools where they demonstrably enhance readiness, while ensuring transparency, consent, and safeguards that protect the human at the center of the system.

## REFERENCES

- Armendariz, N. & Walcutt, J.J. (2022). Re-Engineering Aviation Training: Applying human-focused learning engineering processes to modernize training pathways, interventions, and use of simulation. Paper presented at ModSim World.
- Balconi, M., & Crivelli, D. (2020). Neurophysiology of visual-motor learning during simulated tasks: Implications for training and evaluation. *Frontiers in Virtual Reality*, 1, Article 754627. <https://doi.org/10.3389/frvir.2020.754627>
- Department of Defense. (2020). DoDI 5000.87: Operation of the Software Acquisition Pathway. Office of the Under Secretary of Defense for Acquisition and Sustainment.
- Dugan, E., & Baloi, A. (2022). Human Factors and Medicine Panel (HFM-311): NATO Research Task Group Final Report on Human Systems Integration. NATO Science and Technology Organization.
- Korean Neurological Association. (2021). Clinical practice guidelines for intraoperative neurophysiological monitoring: 2020 update. *Annals of Clinical Neurophysiology*, 23(1), 35-45.
- Mulready-Stone, R. (2024). Redefining military education: The imperative for outcomes-based military education. *Joint Force Quarterly*, (112), 30–38.
- Office of Naval Research (ONR). (2006). Augmented cognition: Enhancing human performance in complex environments. Department of the Navy.
- Parker, G., Armendariz, L., & Walcutt, J. (2023). Neural activity mapping of Army aviation flight task performance. In Proceedings of the Interservice/Industry Training, Simulation, and Education Conference (IITSEC).
- Parker, C., Armendariz, N., Walcutt, J.J., Jeyanandarajan, D., & Momeny, L. (2023). Neural Activity Mapping of Army Aviation Flight Task Performance. Paper presented at IITSEC.
- Parker, C., Walcutt, J. J., & Armendariz, N. (2025). Neural activity patterning by learning modality in military training. Proceedings of the IT<sup>2</sup>EC Technical Paper Presentation/Panel, Oslo, Norway.
- Prinzel III, L. J. (2002). Research on hazardous states of awareness and physiological factors in aerospace operations (No. NASA/TM-2002-211444).
- See, J.E. (2021). Human readiness levels explained. *Ergonomics in Design*, 29(4), 5–10. <https://doi.org/10.1177/10648046211017410>
- St. John, M., Kobus, D. A., Morrison, J. G., & Schmorow, D. (2004). Overview of the DARPA augmented cognition technical integration experiment. *International Journal of Human-Computer Interaction*, 17(2), 131-149.

- SoLaR (Science of Learning and Readiness) Community. (2020). SoLaR Exemplar Report: Advancing a data ecosystem for learning. Advanced Distributed Learning Initiative. <https://adlnet.gov/assets/uploads/SoLaR-Exemplar%20Report%2020200422.pdf>
- TEM Journal. (2022). Evaluation of a field-ready neurofunctional system in operational learning environments. *TEM Journal*, 11(3), 1227–1233. <https://doi.org/10.18421/TEM113-29>
- U.S. Army Research Laboratory. (2008). ARL-SR-0333: Effectiveness evaluation research outline. Aberdeen Proving Ground, MD.
- Vierling, R., Schatz, S., LaFleur, B., & Lyons, L. (2018). Neurophysiological monitoring for adaptive aviation training. In *Proceedings of the Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC)*.
- Walcutt, J.J. & Armendariz, N.J. (2021). Personalized Neuro-informed learning and the New Role of Instructors as Facilitators, iFest.
- Walcutt, J.J. & Jeyanandarajan, D. (2021). Objective neurological measurement for learning: A review, I/ITSEC.
- Walcutt, J.J. & Jeyanandarajan, D., (2020). Neuro-optimization in ADL Environments. Paper presented at ADL iFest.
- Walcutt, J. J., & Schatz, S. (2018). Modernizing learning: Building the future learning ecosystem. Advanced Distributed Learning Initiative, Department of Defense.
- Walcutt, J. J., Schatz, S., LaFleur, B., & Lyons, L. (2023). Personalized learning strategies in military training environments. In *Proceedings of I/ITSEC 2023*.
- Walcutt, J.J., Armendariz, N., & Jeyanandarajan, D. (2021). Neuro-informed Learning: The Next Frontier. Chapter in *Education 3.0 and eLearning Across Modalities*.
- Wickens, C. D., Goh, J., Helleberg, J., Horrey, W. J., & Talleur, D. A. (2008). Attentional models of multi-task pilot performance using advanced display technology. *Human Factors*, 45(3), 360–380. <https://doi.org/10.1518/hfes.45.3.360.27250>