Predicting the Human Factor: Data-Driven Talent Identification and Training Optimization

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ABSTRACT

Achieving operational dominance requires advanced training and education strategies that incorporate cutting-edge insights from neuroscience, physiology, and policy. This paper introduces a data-driven framework using modeling and simulation to optimize human performance across diverse operational contexts. Drawing from organizational psychology, clinical psychology, instructional design, neuroscience, and human factors, our approach customizes training interventions to match individual cognitive and physiological profiles. Aligning training policies with empirical evidence ensures measurable improvements in operational readiness and effectiveness.

Our methodology centers on strategically utilizing neuroscience and physiological data—such as real-time biometrics and cognitive workload indicators—to refine training protocols and guide policy-making. Modeling and simulation tools accelerate the development and iteration of training programs, enabling stakeholders to quickly identify optimal training paths. Furthermore, these insights equip leaders and policymakers to make informed, targeted investments in training that enhance sustained human performance.

By integrating best practices across multiple disciplines, we effectively bridge theory and practical application. This paper demonstrates how a comprehensive, policy-driven training strategy develops agile, resilient warfighters capable of maintaining superiority in complex environments. We present case studies illustrating successful implementations, outcomes, and policy implications within real-world defense scenarios. Our findings highlight the necessity of combining evidence-based instructional design, advanced modeling and simulation techniques, and data-informed policies to sustain operational excellence.

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THE CASE FOR EVOLUTION IN TRAINING

From the cockpit to the command post, the operational demands placed on military personnel today far exceed the linear instructional assumptions of yesterday. Our warfighters now operate in fluid, data-saturated environments where adversaries evolve tactics faster than we can codify doctrine. The challenge is not just training proficiency—it is cultivating cognitive agility, physiological endurance, and mission-oriented decision-making that scales from the individual to the joint task force.

The Department of Defense (DoD), recognizing this shift, has outlined in its Modernizing Learning strategy a clear need for a future learning ecosystem—one that emphasizes lifelong learning, system interoperability, and personalized instruction. The future learning environment must be built around learners, not institutions, allowing individuals to access, own, and manage their learning data while navigating seamlessly across formal, informal, operational, and experiential learning domains. These principles directly challenge current institutional frameworks.

Operational aviators have seen firsthand how training that fails to account for mental fatigue, workload variation, or real-time adaptation leaves crews vulnerable in dynamic scenarios. The reliance on legacy frameworks like ADDIE—while necessary for baseline compliance—can result in stagnation. Our institutional processes, though well-intended, often reinforce rigid instructional pathways that do not accommodate neurocognitive or physiological variation across learners.

The introduction of Learning Engineering (LE) into military instructional systems offers a paradigm shift. It’s not about discarding structure; it's about supercharging it with evidence, feedback, and systemic agility. LE aligns directly with the DoD's strategic vision to support modular, portable, and scalable learning pathways. This paper presents LE as the bridge between policy and operational realism—where simulation, data, and neuroscience converge to produce warfighters who aren't just trained but are primed for uncertainty and resilient in execution.

FOUNDATIONS OF LEARNING ENGINEERING AND ADDIE

The ADDIE framework—comprising Analysis, Design, Development, Implementation, and Evaluation—has long served as the instructional systems backbone across military education programs. It is deeply embedded in U.S. Navy and Marine Corps policy through NAVEDTRA 130B/136 and NAVMC 1553.1A, respectively, as well as the USAF through DAFH 36-2675. Its strength lies in its structured, sequential process and enforceable outputs. In aviation units, ADDIE ensures reproducibility, auditability, and standardized training delivery. However, as a system it presumes that performance problems are fixed, that instructional content is static, and that learners follow a uniform path.

In real-world operational settings, these assumptions break down. Instructors are often required to improvise content delivery based on aircraft availability, weather, or mission demands. More critically, learners differ—not only in prior knowledge, but in stress responses, fatigue thresholds, and cognitive endurance. The rigidity of ADDIE leaves no formal room for that variation.

Learning Engineering, in contrast, builds a responsive, data-rich ecosystem around training. It draws from cognitive science, human systems integration, and learning analytics. The TRAP framework—Theoretical, Research-based, Analytical, and Practical—outlines a methodology where instructional design is continuously informed by performance metrics and contextualized by operational realities (Zhang & Zhu, 2023). The IEEE ICICLE model introduces a learning lifecycle of creation, implementation, and investigation—each stage supported by data capture and analysis (Goodell & Kolodner, 2023).

Importantly, Learning Engineering aligns with the broader vision articulated in Modernizing Learning, which calls for the integration of artificial intelligence, xAPI data interoperability, digital credentials, and advanced metadata systems. These tools allow for adaptive instruction, continuous learner modeling, and analytics-informed decision-making at the system and individual level. Wright and Barber (2023) highlight how simulation fidelity and cognitive alignment with real-world complexity improve human performance when built on LE-aligned frameworks. The use of federated machine learning and secure infrastructure, as proposed by Zou et al. (2023), further demonstrates how LE can integrate with modern data ecosystems, allowing dynamic, just-in-time training updates while protecting sensitive operational information.

Where LE excels is in its capacity to inform micro-adjustments: from simulator feedback loops that adapt based on pilot stress signals, to real-time adjustments in task complexity based on biometric load indicators. Policy must evolve to support these flexibilities. Future revisions to NAVEDTRA and NAVMC documentation should institutionalize instrumentation, adaptive learning thresholds, and data-handling protocols that are robust enough to handle both privacy constraints and analytics demands. Within the USAF, the Learning Engineering Center of Excellence is being developed that will similarly support the enterprise-wide transition of this refocus on this more holistic approach the training development. The vision is not just better instruction, but an interconnected and enduring learning architecture that supports lifelong readiness, as envisioned by the Advanced Distributed Learning (ADL) Initiative.

APPLYING LEARNING ENGINEERING FRAMEWORK TO MILITARY TRAINING

The Learning Engineering (LE) framework aligns with the operational requirements of high-risk, time-constrained, and data-rich environments such as Army aviation and Navy flight pipelines. The initial phase focuses on defining learning objectives and performance metrics through operational task decomposition. Techniques such as Mission Essential Task List (METL) analysis, cognitive task modeling, and workload indexing using NASA TLX enable granular mapping of expected performance conditions.

Learner models are constructed through multi-modal data acquisition. This includes neurocognitive evaluations (e.g., Go/No-Go tasks, psychomotor vigilance tests), baseline physiological readings (e.g., resting HRV, SpO_2 variability), and self-assessments (e.g., Grit Scale, NEO-PI). In operational units, additional data is gathered from embedded simulation platforms, instructor assessments, and telemetry logs from synthetic training environments.

Sensor systems are integrated within the training environment, utilizing devices such as EEG headsets, eye-tracking modules, and wearable physiological monitors. These systems enable real-time detection of attentional states, visual scan patterns, and biometric load fluctuations. Data streams are synchronized with task timelines to enable cross-referencing with instructional milestones. This supports adaptive feedback mechanisms at both the individual and group levels. Feedback is necessary and applies reasoning to the correct/incorrectness of learner's actions, and are explicit instructional support to guide their learning experience (Vogel-Walcutt, Fiorella, & Malone, 2013) versus data which is not interpreted for the learner.

Tools such as STEEL-R—an extension of the Total Learning Architecture (TLA)— can enable this infrastructure. It uses xAPI data standards and a federated Learning Record Store (LRS) to aggregate inputs across devices and platforms. This permits both real-time instructional adaptation and retrospective analysis at the enterprise level. Instructors, commanders, and curriculum designers all gain access to performance trends and predictive learning trajectories (Hernandez et al., 2022).

The final—and most powerful—component is policy coupling. LE is only as effective as the latitude instructional leaders have to act on its insights. Curriculum control documents (CCDs), Training Task Inventories (TTIs), and instructor syllabi must be modular enough to permit LE-driven adjustments without triggering re-certification delays or compliance audits. This last piece would require a complete shift in the understanding of how curricula are developed across the services, moving to an adaptable model instead of a rigid industrial one which has been in place since the 1940s. Instead, as seen in the recent Russia-Ukraine conflict, what is needed is a rapidly acquisitioned, mass customized, and quick-to-deploy product which can be scaled or tailored to a unit to meet their operational need (Presnall, Nickolaus, & Banks, 2025).

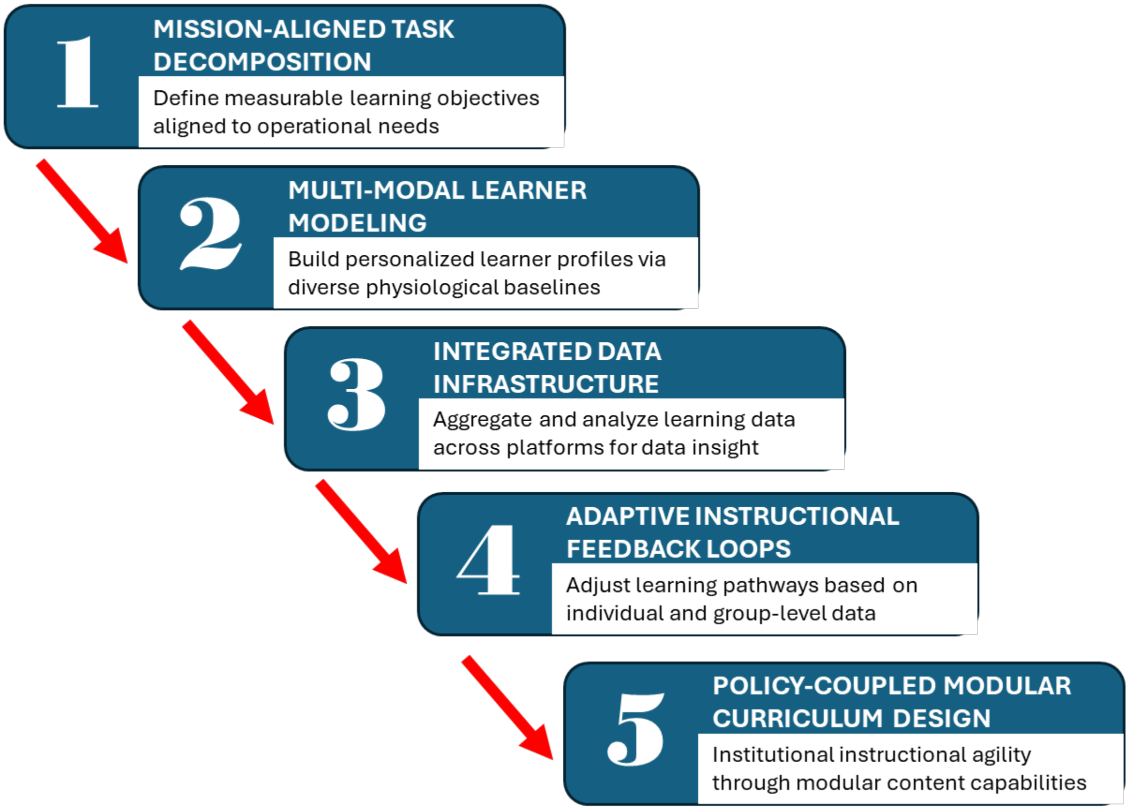

Figure 1. Aligning Personalized Data-Driven Learning Throughout the Learning Experience

CASE STUDIES AND THOUGHTS FOR APPLICATIONS

Army Aviation Cognitive Workload Initiative

The project by Parker, Armendariz, and Walcutt (2023), conducted at an Army aviation unit, aimed to modernize mission readiness training using biometric-informed instructional design. Specifically, the team sought to identify cognitive workload thresholds during critical rotary-wing flight tasks in degraded visual environments (DVEs). Their objective was to correlate biometric stress responses with task phases to better align instructional pauses and scenario complexity with physiological readiness.

The researchers collected data from over a dozen rotary-wing aviators through a series of flight simulator runs replicating DVE mission profiles. Data streams included electroencephalogram (EEG) activity captured using dry, non-contact EEG sensors. The EEG was focused on detecting changes in alpha, beta, and theta wave activity across flight tasks, particularly during periods of rapid task switching or unexpected visual transitions.

Due to equipment issues, the original soft-form EEG headset was replaced with a rigid-frame version, which provided a stable fit but no additional physiological sensors. No chest harnesses or HRV monitors were used in the data collection. The EEG headset operated without conductive gel, using dry electrode contact and was synced with simulator timelines via a custom integration tool. Observers concurrently tracked simulator performance and manually annotated timeline events to align with the EEG data stream.

Signal quality was evaluated using time-domain signal consistency and dropout rates. Approximately 85% of the sessions produced high-quality EEG traces suitable for analysis. The most significant workload indicators appeared during rapid altitude transitions, low-visibility maneuvering, and mission-critical decision-making phases.

Based on these findings, instructors revised training scripts to introduce pause points aligned with workload spikes and inserted guided reflection segments following high-cognitive-load tasks. Additionally, summary EEG visuals were incorporated into debriefs to help learners understand their personal workload profiles. This implementation supported a move toward real-time instructional responsiveness and data-driven learner self-awareness.

Biosensor Study in Operational Environments

Hunt et al. (2023) deployed a multimodal biosensor suite to assess physiological and cognitive readiness in British Army personnel during field exercises. The goal was to evaluate the feasibility of live physiological monitoring in austere environments and identify physiological stressors that may compromise performance or learning.

The study involved over 100 soldiers participating in two-week long training events under high physical and environmental stress. Data collected included heart rate, sleep patterns, hydration levels, skin temperature, and galvanic skin response. Tools included chest-worn ECG sensors, wrist-based activity trackers, and hydration bio-patches. A custom telemetry system streamed data to mobile base stations for aggregation.

The sensors performed reliably in 87% of recorded sessions. Environmental interference and movement occasionally impacted signal integrity, but redundancy across modalities (e.g., sleep validated by both HR patterns and activity logs) maintained overall data fidelity. Quality assurance protocols were embedded into daily tech-check routines by medics and instructors.

Crucially, the team was able to translate the biometric data into actionable insights. Units that experienced elevated cumulative stress scores were more prone to communication breakdowns and task omissions. Commanders used this feedback to rotate personnel, adjust task loads, and revise sleep cycles during subsequent missions. The successful use of data as a leadership tool reinforced the viability of biosensor integration into force readiness monitoring.

EEG into Physiology

Several studies at the Naval Aeromedical Research Laboratory (NAMRL) have used EEG to detect impairments in sensory, cognitive, and motor function, as well as decision-making, resulting from extreme aerospace environmental exposures such as hypoxia. In a recent example, Weatherbie et al. (2024) investigated the sensitivity of neurocognitive markers and cognitive performance during a mask-off, acute normobaric hypoxia exposure, comparing it to a normoxic condition. Thirty-one male participants completed two study visits: one involving normoxic exposure (21% O_2) and the other an acute hypoxic exposure (10.6% O_2), each lasting up to 45 minutes in a normobaric hypoxia chamber. Specifically, after the 45-minute acute hypoxic exposure, the researchers observed a slower reaction time on the psychomotor vigilance task ($p = 0.002$) and impaired underlying auditory sensory processing, indicated by a significant reduction in the P3a amplitude ($p = 0.005$).

While this research, initially aimed at support developing non-invasive in-flight O2 sensors, offers a powerful opportunity to enhance aviator training simulations, particularly in the context of hypoxia. Instead of using EEG directly in simulations, the data derived from EEG measurements and associated task performance can be used to create a more realistic and effective training environment. This avoids the challenges associated with real-time EEG integration, such as artifact cleaning, the extensive training required for instructors to interpret the data, and the inherent limitations of achieving true real-time feedback. EEG provides objective measures of cognitive and motor function, which are crucial for supplementing the subjective reports of experiences like tingling, hot flashes, dizziness, tunnel vision, and other symptoms (Blacker & McHail, 2022). By leveraging this data, simulation training can better prepare pilots and aircrew to manage the cognitive challenges of hypoxia, emphasizing a shift away from relying solely on subjective perceptions and reinforcing the importance of regularly monitoring flight instruments such as altitude, heading, and speed indicators.

Furthermore, simulations can be significantly improved by incorporating EEG-derived data to realistically model the impact of hypoxia on specific tasks. This approach allows for the development of targeted training scenarios designed to accelerate skill acquisition through the exploration of different cognitive demand management strategies, fostering a more engaging and effective learning experience. Identifying and addressing individual performance weaknesses within the safe and controlled simulation environment ensures that pilots and aircrew are better prepared to maintain optimal performance under pressure in real-world hypoxic situations.

In essence, leveraging objective data from EEG studies to inform the design and implementation of flight simulations has the potential to revolutionize pilot and aviator training. By creating more realistic and challenging scenarios, simulations can foster better cognitive strategies, accelerate skill acquisition, and ultimately enhance flight safety, sidestepping the practical difficulties of incorporating EEG as a live biofeedback mechanism.

Army Data-Driven Operational Training Experiment

The Army pilot described by Schwille, Fisher, and Albright (2023) aimed to operationalize real-time data feedback during a brigade-level field training exercise. The intent was to move beyond after-action reviews by embedding analytic capability into the exercise itself—surfacing command decision performance and cognitive load indicators during live mission events.

Data were collected from more than 250 participants using GPS trace logs, radio transmission recordings, behavioral tagging via observer teams, and decision-point timing metrics. Communications were parsed through natural language processing tools to flag hesitation, uncertainty, or deviation from doctrinal phrasing. GPS logs were used to reconstruct maneuver timelines, identify command delays, and map deviation from assigned routes.

Collection tools included tactical radio intercept software, tablet-based observer tagging forms, and personnel-tracking smart cards. All data were fed into a centralized fusion platform that integrated time, location, decision, and communication markers. Data fidelity was rated high, with missing packets under 10%, primarily during long-range operations or signal obscuration.

The integration of this data allowed the brigade staff to visualize friction points mid-exercise and deploy instructional assets (coaches, mentors, intelligence injects) accordingly. Commanders reported increased clarity in identifying what cognitive factors led to mission drift or tactical stalls. Importantly, this real-time use of data served as a model for building training exercises that serve both instructional and operational insight generation.

US Air Force Human Weapon System Programs and Technology Transfer

The U.S. Air Force's concept of the "Human Weapon System" reflects a fundamental recognition: that aircrew and support personnel are not simply operators of complex systems, but integrated components of the system itself. Optimizing human performance, therefore, becomes as mission critical as maintaining aircraft or upgrading avionics. The Air Force has launched multiple initiatives aimed at enhancing human readiness through targeted cognitive, physiological, and behavioral support.

One such initiative is the 33rd Operations Support Squadron's Human Performance Program, which provides F-35A pilots access to embedded physical therapists, strength coaches, and performance specialists. The program's goal is to reduce musculoskeletal injuries, increase fatigue resilience, and promote long-term pilot retention. Equally important is the program's data strategy: biometric and injury tracking are embedded into the flight routine. Metrics on strength imbalances, recovery profiles, and strain load are fed into dashboards that inform both the individual pilot and leadership decisions about workload and scheduling. This embedded feedback loop echoes Learning Engineering (LE) principles, turning human performance into a continuously monitored and optimized variable.

Another example is the B-52 Formal Training Unit (FTU) at Barksdale AFB, which has adopted the Comprehensive Readiness for Aircrew Flying Training (CRAFT) program. CRAFT focuses on integrating nutrition, stress resilience, and cognitive agility into the training pipeline. Its implementation includes real-time biometric monitoring, sleep tracking, and cognitive workload assessments. Importantly, CRAFT uses this data not only for after-action analysis, but for live adjustments to training protocols, recovery cycles, and cognitive task loads. Instructors, performance coaches, and flight leadership share a common dashboard to assess and iterate training based on current human systems readiness.

Supporting this cultural shift, a RAND Corporation study (Yonekura, Toukan, Marler, Abler, Hargrove, Ro, Winston & Kumar, 2024) outlines key enablers and barriers in the transition of advanced training technologies within the Air Force. The study identifies modular architectures, agile development processes, and mission-aligned implementation strategies as critical to enabling rapid transition. It also notes that alignment with operational requirements, consistent funding, and leadership advocacy are essential to sustain innovation. These insights mirror the structural elements needed to implement effective Human Weapon System programs at scale.

The convergence of RAND's institutional analysis and real-world HWS implementations represents a broader LE-compatible strategy: gather rich human performance data, integrate it through interoperable systems, and use it to drive real-time, learner-centered adaptation. In both the B-52 CRAFT and 33rd OSS initiatives, we see practical application of these ideas. Not only is human data being gathered—it is being transformed into utility. Training schedules are adapted, recovery programs are individualized, and long-term career viability is actively managed based on physiological insight.

This blended model of technology transition and human-centric performance design represents a scalable path forward. As new training technologies emerge—particularly those related to virtual reality, AI-enhanced debriefs, and biofeedback-enabled simulation—programs like CRAFT and the OSS initiative offer a replicable pattern: integrate, evaluate, adapt, and reinvest. The LE framework serves not only as a design philosophy, but as a strategy to harmonize operational performance with instructional innovation.

DISCUSSION: OPPORTUNITIES AND CHALLENGES

Despite the promising trajectory of Learning Engineering in military contexts, its adoption faces several structural and operational hurdles. First, legacy infrastructure presents a technical limitation. Many simulators, training environments, and LMS platforms lack the data instrumentation required for biometric capture or do not support open standards like xAPI. The result is an architecture unable to support continuous data capture or meaningful interoperability between systems. This, however, highlights the importance of those in development to be amenable to these changes in the future. It is far too costly to try and modify a system later, when adopting standards now can improve availability in the future to update instrumentation or connectivity.

Second, there is a notable shortage of personnel trained in both instructional systems design and data analytics. While the military has a robust instructional cadre, few members possess the technical acumen needed to manage biometric data or apply learning science models in real-time. Upskilling this workforce will require new training pipelines, certifications, and cross-disciplinary billets that embed psychologists, data scientists, and operational experts in training development units.

Third, ethical and privacy concerns remain unresolved. The use of biometric and neurocognitive data in training raises legitimate questions about consent, data ownership, and long-term usage. Policies must be developed to protect service members' physiological data from misuse while allowing for aggregated insights that can inform training system design and policy decisions.

Fourth, cultural inertia slows adoption. Units familiar with existing processes often resist experimentation, particularly when new methodologies appear to challenge legacy authority structures. Effective change management strategies must include operational champions, evidence-based demonstrations, and incremental implementation plans that reduce perceived risk.

Fifth, funding mechanisms remain misaligned with iterative development models. Most training systems are procured and validated under milestone-based acquisition processes that prioritize final delivery over continuous improvement. Learning Engineering thrives under agile development cycles—ones that permit phased learning deployment, modular upgrades, and continual refinement of content based on real-world data. Acquisition policy must be revised to enable these models.

Finally, as Mishra et al. (2023) argue in their operational readiness model, future architectures may depend on AI-enabled learning systems and predictive monitoring. LLMs and multimodal data fusion, they contend, could dynamically assess mission readiness and skill gaps in real-time, but only if data policies and system integration allow for secure, ethical application of those capabilities.

CONCLUSION

Learning Engineering offers a powerful enhancement to traditional instructional design in military contexts. By integrating modeling and simulation, neuroscience, and real-time data collection, LE enables training that is both policy-compliant and operationally responsive. Case studies from Army aviation and field exercises show that the approach is viable and impactful. Future efforts should focus on institutionalizing LE practices, investing in secure data infrastructure, and aligning policy incentives to reward data-informed instructional innovation.

The integration of adaptive technologies and human-centered learning systems marks a fundamental shift in how the military prepares its personnel. While ADDIE provides structure, LE provides strategy—a way to respond to emerging challenges with instructional precision and evidence-backed agility. This paper argues that the future of military readiness lies in the partnership between policy and practice, and in the engineering of learning environments that evolve as quickly as the missions they support.

As noted in Goodell's broader LE implementation guide and reflected in early DOD-adjacent pilot studies (Goodell & Kolodner, 2023), momentum is building toward institutional reform. The ongoing synthesis of modeling, human systems integration, and applied cognitive science promises a future where military learning is both evidence-based and deeply operationally relevant.

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