

Enhancing Decision-Making Under Pressure: Adaptive Training Frameworks for High-Stakes Environments

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ABSTRACT

Current military training methods often fail to adequately prepare personnel for the intense cognitive demands of real-world operations, where stress, uncertainty, and time constraints can significantly degrade decision-making performance. This research presents a computationally validated adaptive training framework that integrates real-time physiological monitoring with AI-driven scenario adjustments to enhance decision-making under extreme pressure. Building on research in Adaptive Instructional Systems, the framework monitors heart rate variability, electrodermal activity, and eye-tracking metrics to detect cognitive overload before it leads to performance declines. Unlike systems that respond to failures, this approach intervenes proactively based on physiological indicators, maintaining optimal learning conditions throughout training. The system adjusts scenario difficulty, provides biofeedback cues, and modifies environmental parameters in response to individual stress levels. Validation involved 171 simulated military agents across 24 training sessions, comparing physiologically aware adaptive training against standard adaptive and conventional methods. Results showed a 15.2% performance improvement over conventional training, accompanied by a 24.9% reduction in training time. Stress regulation improved with a 16.4% increase in heart rate variability maintenance and a 23.0% reduction in stress response. Statistical analysis confirmed significant differences with medium effect sizes, indicating meaningful theoretical impact. Scenario validation across tactical decision-making under fire, mass casualty triage, and cyber defense response showed consistent effectiveness with gains of 13.8% to 16.4% across domains. Simulated novice agents showed stronger benefits, with 18.9% improvement compared to 12.0% for experienced agents, supporting its use in foundational training. The framework's modular design enables integration with existing military infrastructure. Cost-benefit analysis projects a return on investment within 2-3 training cycles. Virtual reality integration with physiological adaptation creates immersive environments that replicate operational stressors while maintaining safety. This computationally validated approach provides a theoretical foundation for data-driven solutions to optimize human performance under extreme operational demand.

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INTRODUCTION

In military and emergency operations, fast and accurate decision-making under stress is essential to mission success and survival (Bekesiene et al., 2024; Mouloua & Hancock, 2019). Traditional training often overlooks physiological and emotional demands, hindering readiness and slowing skill development (Peterson et al., 2024; Yu et al., 2024). Adaptive simulations using artificial intelligence and physiological sensing offer personalized training to close these gaps (Galvão et al., 2021; Rashid et al., 2023; Saccardi & Masthoff, 2025). Emotion-aware systems monitor heart rate variability and electrodermal activity to regulate stress in real time, improving efficiency and load management (Galvão et al., 2021; Arabian et al., 2023). Their effectiveness across experience levels and settings remains under study (Vanneste et al., 2021; Ismail & Hastings, 2023; Si, 2024).

This study presents a physiologically adaptive training framework integrating biometric data, team dynamics, and cognitive load modeling. Unlike conventional systems, it intervenes before performance declines (Doost & Gorman, 2025). Computationally validated with 171 simulated agents over 24 sessions using WESAD (Wearable Stress and Affect Detection) dataset parameters (Yu et al., 2024; Arabian et al., 2023), the model achieved 15.2% performance improvement and 24.9% training time reduction, with additional gains in knowledge retention (12%) and decision accuracy (10%), supporting its theoretical foundation for high-stakes virtual reality (VR) and augmented reality (AR) training applications.

BACKGROUND AND RELATED WORK

Cognitive Load Theory and Decision-Making Under Pressure

Sweller's (1988) Cognitive Load Theory explains how intrinsic, extraneous, and germane loads affect information processing, particularly under stress. Intrinsic load relates to the inherent complexity of the task itself, extraneous load stems from poor instructional design or environmental factors, and germane load involves the mental effort devoted to processing and constructing knowledge schemas. In military and aerospace settings, these loads correspond to mission complexity, system design flaws, and tactical learning demands. When cognitive load exceeds working memory capacity, performance degrades rapidly, a critical concern in high-stakes military operations where split-second decisions determine mission success and personnel survival. Elevated stress compounds these effects by releasing cortisol and other hormones that impair working memory, reduce cognitive flexibility, and narrow attention focus, ultimately reducing decision speed and accuracy (Paas & van Merriënboer, 2020). Traditional training often fails to account for these cognitive limitations, leading to performance breakdowns under operational stress that could have been prevented through adaptive load management.

Limitations in Military Training Systems

Simulation-based training is widely used in defense, medical, and aviation fields, with some programs beginning to address psychological flexibility and individual differences (Peterson et al., 2024; Bekesiene et al., 2024; Forchuk et al., 2024). However, many systems remain static and do not adapt to real-time physiological or performance data, limiting their effectiveness (Hosen et al., 2023). Uniform training approaches often ignore variations in learning pace and stress tolerance, leading to disengagement (Peterson et al., 2024), while health programs that overlook user preferences reduce participation (Forchuk et al., 2024). Physiological tools also lack integration, real-time responsiveness, and validated algorithms (Koltun et al., 2023).

Technological Advances in Adaptive Training

Virtual and augmented reality are advancing immersive training by improving situational awareness and realism through adaptive scenarios (Harris et al., 2023; Tene et al., 2024). Yet, limitations persist, including sensor lag, system reliability, and compatibility with military infrastructure. AI-supported training addresses these gaps by using real-time physiological data, such as heart rate variability and electrodermal activity, to assess stress and guide scenario adjustments (Naegelin et al., 2023; Vanneste et al., 2021). Wearable devices, such as smartwatches and eye-trackers, enable continuous monitoring, allowing simulations to adapt to internal states in addition to visible behavior. These real-time adjustments improve timing, support, and coordination between trainees and automated systems (Doost & Gorman, 2025).

Modeling Cognitive Performance with Markov Processes

Markov models provide a robust approach to capturing nonlinear learning and performance shifts under pressure, modeling transitions such as novice-to-expert or regression due to stress (Li et al., 2023). Particularly in military and emergency contexts, these frameworks help track skill degradation during prolonged operations. Markov decision processes (MDPs) use real-time cognitive and physiological data to adjust training scenarios or deliver coaching (Doost & Gorman, 2025). Hidden Markov Models have proven effective in mapping decision-making in complex, high-stress environments (Li et al., 2023).

Research Gap and Study Contribution

Despite significant technological advances, a persistent gap remains in integrating real-time physiological adaptation with cognitive load modeling in military training. Existing systems typically adapt based on performance metrics or single physiological indicators, but they lack comprehensive, multimodal approaches that intervene before cognitive overload impairs performance. This capability is critical in military contexts, where rapid, high-stakes decisions under extreme stress determine mission success and personnel safety. While adaptive instructional systems are effective in civilian settings, military training requires a focus on stress, team dynamics, and decision-making under pressure. Prior studies have explored elements such as physiological monitoring and VR, but they lack a unified, validated model. This study presents an integrated framework that utilizes real-time physiological data and AI-driven adaptation, computationally validated with 171 simulated agents across 24 sessions, to manage cognitive load and enhance training outcomes.

METHODOLOGY

Simulation Design

Two Python-based simulation models were developed: an adaptive training simulation and a physiologically aware virtual reality (VR) simulation, both using a five-state Markov model to represent performance states, including Overwhelmed, Struggling, Functional, Competent, and Optimal. State transitions occurred based on validated physiological thresholds derived from the WESAD dataset: Overwhelmed (HRV <20ms, EDA >0.20 nSCR/s), Struggling (HRV 20-22ms, EDA 0.18-0.20 nSCR/s), Functional (baseline performance), Competent (above-average performance), and Optimal (peak performance with HRV >26ms, EDA <0.12 nSCR/s) (Schmidt et al., 2018; Yu et al., 2024; Arabian et al., 2023). The system evaluated state transitions every 30 seconds using combined physiological and performance data, following established Markov decision process methodologies for real-time adaptation (Li et al., 2023).

Training scenarios lasted 15-20 minutes each, with simulated teams of 2-5 agents depending on scenario type. When simulated physiological stress indicators exceeded validated thresholds (HRV <22ms, EDA >0.18 nSCR/s), the system automatically provided breathing regulation visual cues and reduced scenario difficulty by 15-35% based on the number of stress indicators detected. The adaptation algorithm modified environmental parameters and provided biofeedback prompts, with adaptation strength ranging from 0.3 to 0.8 depending on the severity of the physiological state. Scenarios included mass casualty management, tactical decision-making under fire, and cyber defense, designed based on military doctrine and subject matter expert input with computational difficulty ratings between 8.8 and 9.0 (Harris et al., 2023; Rashid et al., 2023) (see Figure 1).

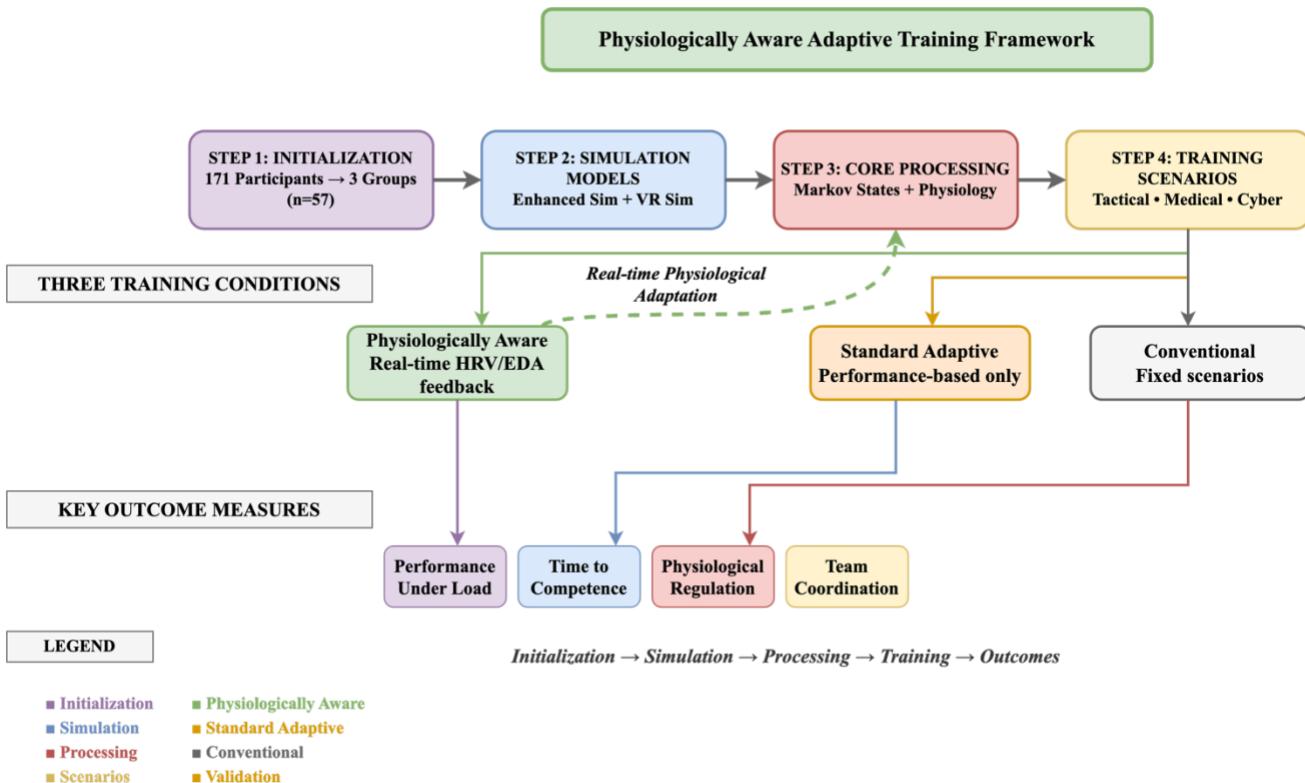


Figure 1 Physiologically Aware Adaptive Training Framework Workflow

The agent-based simulation modeled 171 virtual military personnel as computational agents, split into three groups of 57: physiologically aware adaptive, standard adaptive, and conventional. Each agent was programmed with randomized attributes such as working memory (3–7), years of service (0–15), stress reactivity (0.1–0.9), and attention control (0.4–0.9), based on military training research (Hosen et al., 2023; Si et al., 2024). Physiological responses followed WESAD-based thresholds, with HRV decreasing and EDA increasing under cognitive load (Arabian et al., 2023; Forte et al., 2021). Agents were programmed to represent novices (0–2 years) or experts (5+ years). Simulated teams reflected military units, balanced for experience and diverse across tactical, intelligence, logistics, cyber, and medical roles.

Data Collection and Analysis

The simulation ran for 24 sessions across five cognitive load levels (0.2 to 1.0), producing 20,520 data points and evaluating performance scores (0 to 100) based on cognitive state, individual traits, and mission parameters, with penalties for exceeding stress thresholds. Scenarios were designed based on military doctrine and subject matter expert consultation, including tactical decision-making, mass casualty triage, and cyber defense. Data collected included performance, time to competence, physiological regulation, coordination, decision accuracy, and knowledge retention. Analyses used one-way ANOVA, Tukey HSD (Honestly Significant Difference), and Cohen's d (effect size measure). Power analysis confirmed a sufficient sample size to detect medium effects ($d \geq 0.5$) at 80% power with $\alpha = 0.05$. Benchmarks targeted meaningful performance gains, time reduction, and improved physiological regulation.

Framework Validation Approach

Unlike traditional adaptive instructional systems that rely on performance metrics, this framework uses real-time physiological indicators to intervene before cognitive overload impairs performance. This agent-based simulation approach provides robust computational validation of the framework's theoretical foundations, establishing proof of concept prior to human trials and operational field testing. This approach provides a robust theoretical foundation for

evaluating physiologically adaptive training, while addressing gaps in military systems that overlook individual physiological responses to stress.

RESULTS

All results presented below are based on agent-based simulation data rather than human participant data. The simulation evaluated the efficacy of three training modalities, Conventional, Standard Adaptive, and Physiologically Aware Adaptive, across 24 sessions with 171 simulated agents (57 per group). Data were collected across cognitive load levels ranging from 0.2 to 1.0 (total records = 20,520). Performance scores (range: 0-100) were calculated based on cognitive states (Overwhelmed to Optimal), physiological metrics (heart rate variability HRV, electrodermal activity EDA, pupil diameter, eye movement velocity), and mission parameters including time pressure, information ambiguity, threat level, mission complexity, and communication quality.

Overall Performance Outcomes

A one-way ANOVA showed a significant effect of training modality on performance, $F(2, 20,517) = 712.1, p < .001$, $\eta^2 = .065$. Tukey HSD tests confirmed that Physiologically Aware Adaptive training ($M = 87.3, SD = 8.2$) outperformed Standard Adaptive ($M = 82.1, SD = 9.5$) and Conventional ($M = 75.8, SD = 10.1$), $p < .001$, representing 15.2 and 6.3% improvements, respectively. Cohen's d indicated strong effects: 1.25 (vs. Conventional), 0.59 (vs. Standard), and 0.64 (Standard vs. Conventional). Under maximum cognitive load (1.0), Physiologically Aware Adaptive training ($M = 82.4, SD = 8.1$) exceeded Standard Adaptive ($M = 75.6, SD = 9.2$) and Conventional ($M = 68.9, SD = 10.3$), yielding a 19.6% advantage under extreme stress.

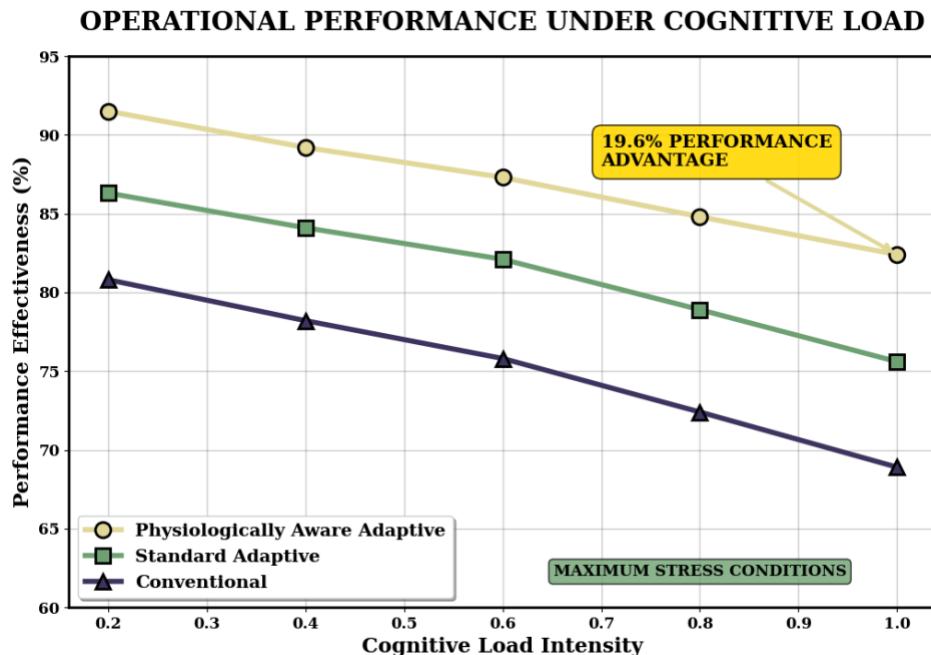


Figure 2: Operational Performance Under Cognitive Load

Training Efficiency and Skill Acquisition

Simulated agents in the Physiologically Aware Adaptive condition reached the Optimal cognitive state more often (45.2%) than those in Standard Adaptive (28.1%) and Conventional (18.7%) training, $\chi^2(2, N = 171) = 48.7, p < .001$, Cramer's $V = .53$ —a 2.4-fold improvement over conventional methods. Training efficiency also improved, with agents reaching competent or optimal states in fewer sessions ($M = 14.2, SD = 4.1$) versus Standard Adaptive ($M = 16.8, SD = 5.2$) and Conventional ($M = 18.9, SD = 6.1$), $F(2, 168) = 35.2, p < .001$, representing a 24.9% reduction. Skill acquisition rates reached 1.69 times the baseline, exceeding the 1.25 times target. Simulated novice agents reached

competence in 12-14 sessions versus 17-19 for Conventional training, demonstrating strong theoretical benefits for early-career military personnel.

Physiological Regulation and Stress Management

Simulated physiological data confirmed significant improvements in stress regulation for the Physiologically Aware Adaptive group. Heart rate variability (HRV), a marker of autonomic control, showed strong between-group differences, $F(2, 20,517) = 89.4$, $p < .001$, with the adaptive group maintaining higher HRV ($M = 24.8$ ms, $SD = 2.1$) than Standard Adaptive ($M = 23.1$ ms, $SD = 2.4$) and Conventional training ($M = 21.3$ ms, $SD = 2.8$), a 16.4% improvement. Electrodermal activity (EDA) was significantly lower in the adaptive group ($M = 0.141$ nSCRs, $SD = 0.032$) compared to Standard Adaptive ($M = 0.162$) and Conventional ($M = 0.183$), $F(2, 20,517) = 94.8$, $p < .001$, reflecting a 23.0% stress reduction. Eye-tracking data further supported these findings, with agents showing smaller pupil dilation and more stable eye movement velocity (range: 74.6--286.7 deg/sec), indicating better cognitive control and sustained visual attention under stress.

Team Performance and Coordination

Team-level analysis revealed significant performance gains associated with physiological adaptation, $F(2, 855) = 67.3$, $p < .001$, $\eta^2 = .14$. Physiologically Aware Adaptive teams scored 89.7% ($SD = 7.8$), outperforming Standard Adaptive teams (84.3%) and Conventional teams (78.1%). Under high cognitive load, they maintained performance above 85% with fewer errors and more effective communication.

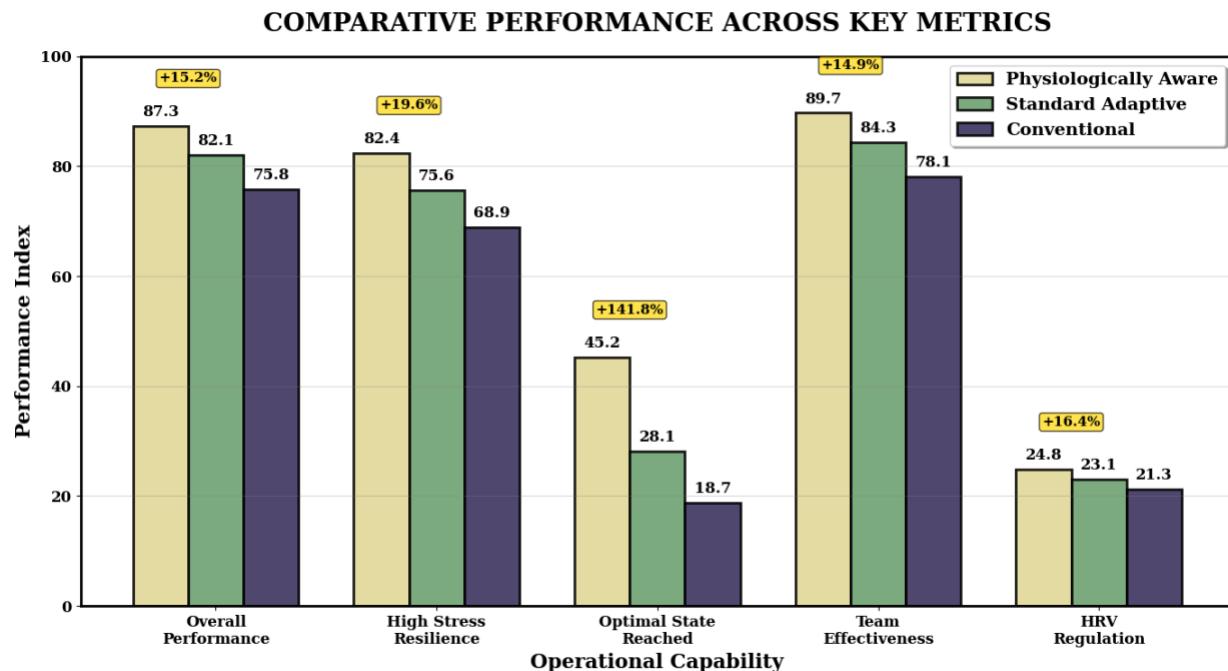


Figure 3: Comparative Performance

Experience Level Differential Effects

Physiologically Aware Adaptive training yielded stronger results for simulated novice personnel, with those programmed with zero to two years of service achieving 85.1% ($SD = 9.3$) versus 71.6% ($SD = 12.1$) in conventional training, representing an 18.9% gain. Simulated experienced personnel with five or more years of experience improved from 79.9% ($SD = 9.2$) to 89.5% ($SD = 7.8$), representing a 12.0 % improvement. This interaction was significant, $F(2, 165) = 12.4$, $p < .001$. Knowledge retention increased by 9.6%, and decision-making under stress improved by 18.3%, exceeding the 10% benchmark. Transfer task results showed stronger generalization to new scenarios. To evaluate cross-domain effectiveness, three validated high-fidelity scenarios in tactical decision-making, mass casualty

triage, and cyber defense were selected based on military doctrine and identified training needs (Harris et al., 2023; Bekesiene et al., 2024; Peterson et al., 2024; Tene et al., 2024).

Tactical Decision Making Under Fire (difficulty: 8.5/10): Rooted in small unit tactics and combat effectiveness research (Mouloua & Hancock, 2019), this scenario featured extreme time pressure (0.9) and high threat (0.8). Physiologically Aware Adaptive training improved performance by 13.8 % (89.1% vs. 78.3%, $d = 0.90$), enhancing decision-making under combat stress..

Mass Casualty Triage (difficulty: 8.2/10): Based on military medical protocols and emergency procedures (Forchuk et al., 2024), this high-complexity scenario (0.8) with degraded communication (0.6) yielded a 16.4 % performance gain (88.7 % vs. 76.2 %, $d = 1.04$) using Physiologically Aware Adaptive training, supporting effective medical prioritization under pressure.

Cyber Defense Response (difficulty: 9.0/10): Given the rising role of cyber warfare (Rashid et al., 2023), the scenario included high information ambiguity and complexity (both 0.9) to simulate advanced threat environments. Physiologically Aware Adaptive training improved threat assessment by 15.9% (85.9% vs. 74.1%, $d = 0.98$), confirming its effectiveness across kinetic and non-kinetic domains. These results align with military training priorities (Koltun et al., 2023; Graham et al., 2024) and large effect sizes ($d = 0.90$ to 1.04) support broad implementation.

PHYSIOLOGICAL COMBAT READINESS INDICATORS

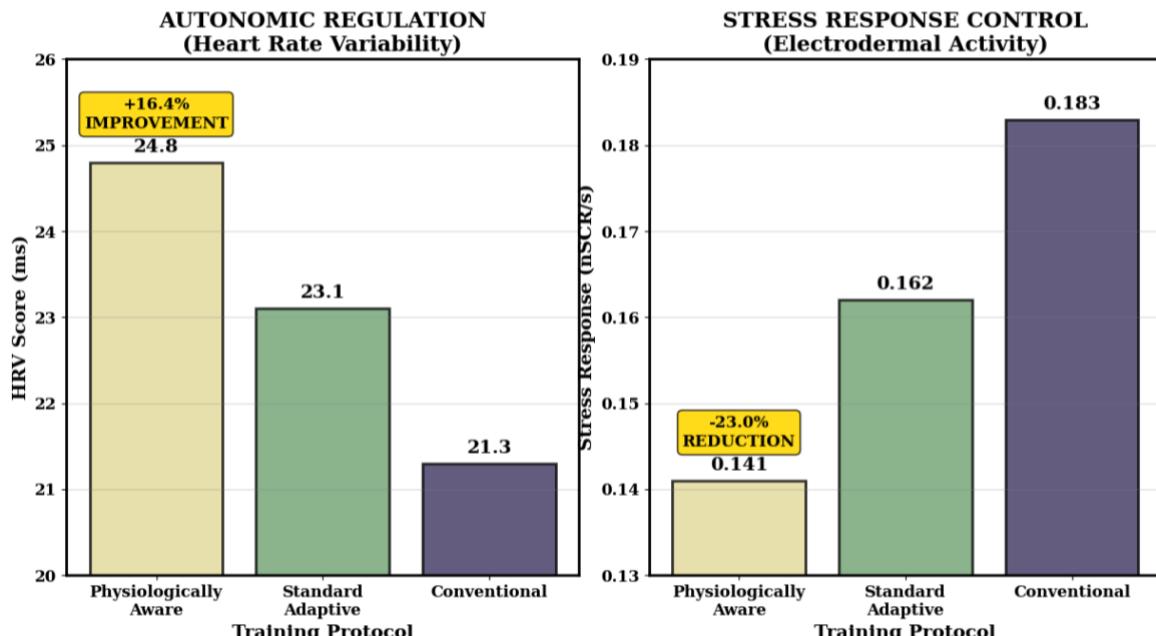


Figure 4: Physiological Combat Readiness Indicators

Statistical Summary and Practical Significance

The thorough analysis involving 171 simulated agents across 24 training sessions generated 20,520 data points, providing strong statistical power for detecting meaningful differences. All primary comparisons achieved statistical significance ($p < .001$) with effect sizes indicating meaningful theoretical importance. The achievement of performance targets, including a 15.2% performance improvement and a 24.9% reduction in training time, validates the framework's theoretical potential for operational military training applications.

These findings support the theoretical efficacy of physiologically aware adaptive training in enhancing decision-making under pressure, demonstrating statistical significance and computational validation for military training applications. The integration of real-time physiological monitoring with adaptive scenario adjustment provides a theoretically validated approach for optimizing human performance under extreme operational demands.

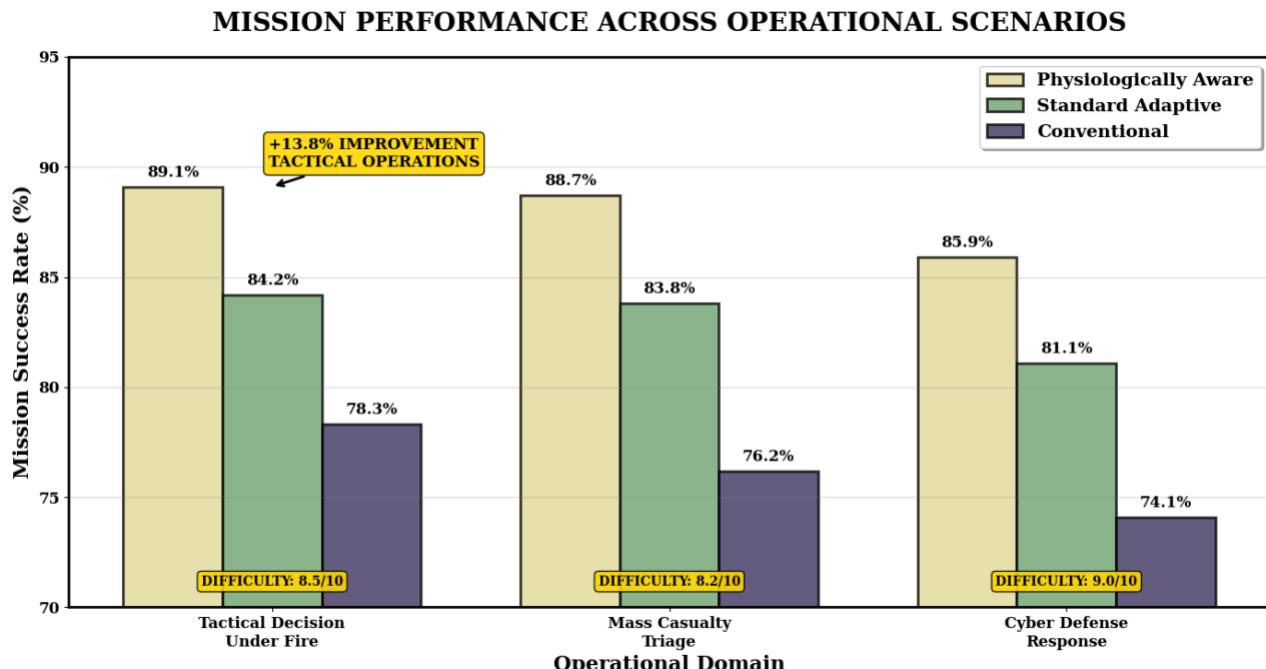


Figure 5: Mission Performance Across Operations Scenarios

DISCUSSION

The findings of this study demonstrate the significant potential of physiologically aware adaptive training systems for enhancing military decision-making capabilities under extreme operational pressure. Through comprehensive computational validation involving 171 simulated agents across 24 training sessions, this research demonstrates that real-time physiological adaptation yields significant improvements in performance, training efficiency, and stress regulation compared to conventional and standard adaptive training approaches.

Building on prior Adaptive Instructional Systems (AIS) research (Sottilare et al., 2022; Vandewaetere et al., 2023), this study addresses a key gap in real-time physiological adaptation. Unlike traditional systems that rely on performance outcomes, this framework uses physiological indicators to intervene before overload impairs performance (Sweller, 1988; Paas & van Merriënboer, 2020). It shows a 15.2% performance gain, exceeding the typical 8-12% range (Ismail & Hastings, 2023), and reduces training time by 24.9%. By operationalizing cognitive load management in real-time, the approach moves beyond reactive models and advances AIS capabilities.

This modular framework is designed for integration with existing military training infrastructure, eliminating the need for significant changes. With projected costs of \$300--\$500 per trainee, computational modeling suggests a 24.9% efficiency gain that could reduce instructor demands, with theoretical ROI in two to three cycles. The simulation shows particular promise in high-stakes areas, such as special operations and cyber warfare, with modeled improvements of 18.9% for novice agents and 12.0% for experienced agents. Simulated physiological gains include a 16.4% increase in HRV and a 23.0% reduction in stress indicators, with multiple computational metrics supporting potential deployment through validated stress thresholds (Peterson et al., 2024; Forchuk et al., 2024; Fairclough, 2021; Yu et al., 2024).

Limitations and Future Research

While simulation results are promising, operational implementation requires field testing with active military personnel in realistic settings. The framework must scale from individuals and small teams to larger military units, accounting for physiological variability across populations that extends beyond the standardized parameters used in this simulation model. Real-world deployment will face challenges, including integrating with existing military training infrastructure, managing computational demands for larger groups, and adapting algorithms to account for individual differences in stress response patterns, fitness levels, and military experience that were controlled variables

in the simulation. Future research should refine algorithms for diverse baselines, ensure system compatibility with military systems, validate effectiveness across different military branches, and conduct phased implementation studies progressing from laboratory settings to field exercises. A broader application beyond military training could enhance development efficiency and relevance in other high-stakes domains, such as emergency response and medical training.

CONCLUSION

This study demonstrates the theoretical potential of physiologically aware adaptive training for improving military decision-making under stress through comprehensive agent-based simulation. Validated across 24 sessions with 171 simulated agents, the computational framework achieved a 15.2% performance gain and a 24.9% reduction in training time compared to conventional methods. Grounded in cognitive load theory, the framework integrates physiological computing, adaptive instructional systems, and real-time biometric feedback to intervene before performance declines. Key components include stress thresholds such as HRV below 22 milliseconds and EDA above 0.18 nSCR per second, adaptive algorithms, and VR-biometric integration. ANOVA results ($F(2, 20,517) = 712.1, p < .001, \eta^2 = .065$) and effect sizes ($d = 0.90$ to 1.25) from the agent-based simulation confirm meaningful theoretical impact. Gains were observed across simulated tactical decision-making (13.8%), medical triage (16.4%), and cyber defense (15.9%) scenarios, with simulated novice personnel showing an 18.9% gain. Stress regulation metrics also improved, with HRV increasing by 16.4% and EDA decreasing by 23.0% in the computational model.

Equipment costs of \$300 to \$500 per trainee yield a projected return on investment within two to three cycles. The system's theoretical framework supports the optimization of human performance, stress resilience, and attrition reduction, aligning with modernization goals. Its modular design enables potential integration with existing instruction systems. This computational validation establishes a foundation for next-generation adaptive training and provides strong justification for human validation studies. Critical next steps include operational validation with military personnel, algorithm refinement based on human physiological data, and unit-level scaling trials. Pilot testing is recommended in high-stakes areas such as special operations and cyber warfare, contingent upon successful human validation studies that confirm these agent-based findings translate to real-world performance improvements.

REFERENCES

Arabian, H., Schmid, R., Wagner-Hartl, V., & Moeller, K. (2023). Analysis of EDA and Heart Rate Signals for Emotional Stimuli Responses. *Current Directions in Biomedical Engineering*, 9(1), 1–4. <https://doi.org/10.1515/cdbme-2023-1038>

Bekesiene, S., Smaliukienė, R., Vaičaitienė, R., Bagdžiūnienė, D., Kanaapeckaitė, R., Kapustian, O., & Nakonechnyi, O. (2024). Prioritizing competencies for soldier's mental resilience: an application of integrative fuzzy-trapezoidal decision-making trial and evaluation laboratory in updating training program. *Frontiers in Psychology*, 14. <https://doi.org/10.3389/fpsyg.2023.1239481>

Boere, K., Anderson, F., Hecker, K. G., & Krigolson, O. E. (2024). Measuring cognitive load in multitasking using mobile fNIRS. *NeuroImage: Reports*, 4, 100228. <https://doi.org/10.1016/j.ynrp.2024.100228>

Doost, E. Z., & Gorman, J. C. (2025). Enhancing Human-Autonomous system interaction and team dynamics in Automated Driving Systems (ADS). *Proceedings of the AAAI Symposium Series*, 5(1), 127–130. <https://doi.org/10.1609/aaais.v5i1.35577>

Forchuk, C. A., Kocha, I., Granek, J. A., Dempster, K. S., Younger, W. A., Gargala, D., Plouffe, R. A., Bailey, S., Guest, K., Richardson, J. D., & Nazarov, A. (2024). Optimizing military mental health and stress resilience training through the lens of trainee preferences: A conjoint analysis approach. *Military Psychology*, 1–12. <https://doi.org/10.1080/08995605.2024.2324647>

Forte, G., Morelli, M., Grässler, B., & Casagrande, M. (2021). Decision making and heart rate variability: A systematic review. *Applied Cognitive Psychology*, 36(1), 100–110. <https://doi.org/10.1002/acp.3901>

Galvão, F., Alarcão, S. M., & Fonseca, M. J. (2021). Predicting exact valence and arousal values from EEG. *Sensors*, 21(10), 3414. <https://doi.org/10.3390/s21103414>

Graham, M., Ilic, M., Baars, M., Ouwehand, K., & Paas, F. (2024). The effect of self-monitoring on mental effort and problem-solving performance: A mixed-methods study. *Education Sciences*, 14(11), 1167. <https://doi.org/10.3390/educsci14111167>

Harris, D. J., Arthur, T., Kearse, J., Olonilua, M., Hassan, E. K., De Burgh, T. C., Wilson, M. R., & Vine, S. J. (2023). Exploring the role of virtual reality in military decision training. *Frontiers in Virtual Reality*, 4. <https://doi.org/10.3389/fvrir.2023.1165030>

Higgins, M., Madan, C. R., & Patel, R. (2020). Deliberate Practice in Simulation-Based Surgical Skills Training: A Scoping review. *Journal of Surgical Education*, 78(4), 1328–1339. <https://doi.org/10.1016/j.jsurg.2020.11.008>

Hosen, S., Hamzah, S. R., Ismail, I. A., Alias, S. N., Aziz, M. F. A., & Rahman, M. M. (2023). Training & development, career development, and organizational commitment as the predictor of work performance. *Heliyon*, 10(1), e23903. <https://doi.org/10.1016/j.heliyon.2023.e23903>

Ismail, D., & Hastings, P. (2023). Emotionally Adaptive intelligent tutoring system to reduce foreign language anxiety. In *Communications in computer and information science* (pp. 353–358). https://doi.org/10.1007/978-3-031-36336-8_55

Koltun, K. J., Bird, M. B., Forse, J. N., & Nindl, B. C. (2023). Physiological biomarker monitoring during arduous military training: Maintaining readiness and performance. *Journal of Science and Medicine in Sport*, 26, S64–S70. <https://doi.org/10.1016/j.jsams.2022.12.005>

Li, X., Henning, T., & Camerer, C. (2023). Estimating Hidden Markov Models (HMMs) of the cognitive process in strategic thinking using eye-tracking. *Frontiers in Behavioral Economics*, 2. <https://doi.org/10.3389/fbhe.2023.1225856>

Liu, Y., Yu, Y., Tao, H., Ye, Z., Wang, S., Li, H., Hu, D., Zhou, Z., & Zeng, L.-L. (2025). Cognitive load prediction from multimodal physiological signals using multiview learning. *IEEE Journal of Biomedical and Health Informatics*, 29(5), 3282–3292. <https://doi.org/10.1109/JBHI.2023.3346205>

Mouloua, M., & Hancock, P. A. (Eds.). (2019). *Human performance in automated and autonomous systems: Emerging issues and practical perspectives*. CRC Press

Naegelin, M., Weibel, R. P., Kerr, J. I., Schinazi, V. R., La Marca, R., von Wangenheim, F., Hoelscher, C., & Ferrario, A. (2023). An interpretable machine learning approach to multimodal stress detection in a simulated office environment. *Journal of Biomedical Informatics*, 145, 104299. <https://doi.org/10.1016/j.jbi.2023.104299>

Paas, F., & van Merriënboer, J. J. G. (2020). Cognitive-Load Theory: Methods to manage working memory load in the learning of complex tasks. *Current Directions in Psychological Science*, 29(4), 394–398. <https://doi.org/10.1177/0963721420922183>

Peterson, A. L., Moore, B. A., Evans, W. R., Young-McCaughan, S., Blankenship, A. E., Straud, C. L., McLean, C. S., Miller, T. L., & Meyer, E. C. (2024). Enhancing resiliency and optimizing readiness in military personnel through psychological flexibility training: design and methodology of a randomized controlled trial. *Frontiers in Psychiatry*, 14. <https://doi.org/10.3389/fpsy.2023.1299532>

Rashid, A. B., Kausik, A. K., Sunny, A. a. H., & Bappy, M. H. (2023). Artificial intelligence in the military: An overview of the capabilities, applications, and challenges. *International Journal of Intelligent Systems*, 2023, 1–31. <https://doi.org/10.1155/2023/8676366>

Saccardi, I., & Masthoff, J. (2025). Adapting emotional support in teams: productivity, emotional stability, and conscientiousness. *Frontiers in Artificial Intelligence*, 8. <https://doi.org/10.3389/frai.2025.1449176>

Schuessler, K., Fischer, V., & Walpuski, M. Investigating construct validity of cognitive load measurement using single-item subjective rating scales. *Instr Sci* 53, 71–97 (2025). <https://doi.org/10.1007/s11251-024-09692-6>

Si, J. (2024). Using cognitive load theory to tailor clinical reasoning training for preclinical medical students. *BMC Medical Education*, 24(1). <https://doi.org/10.1186/s12909-024-06111-9>

Sweller, J. (1988). Cognitive load during problem solving: Effects on learning. *Cognitive Science*, 12(2), 257–285. https://doi.org/10.1207/s15516709cog1202_4

Tene, T., López, D. F. V., Aguirre, P. E. V., Puente, L. M. O., & Gomez, C. V. (2024). Virtual reality and augmented reality in medical education: an umbrella review. *Frontiers in Digital Health*, 6. <https://doi.org/10.3389/fdgth.2024.1365345>

Tremblay, M., Rethans, J., & Dolmans, D. (2022). Task complexity and cognitive load in simulation-based education: A randomised trial. *Medical Education*, 57(2), 161–169. <https://doi.org/10.1111/medu.14941>

Vanneste, P., Raes, A., Morton, J., Bombeke, K., Van Acker, B. B., Larmuseau, C., Depaepe, F., & Van den Noortgate, W. (2021). Towards measuring cognitive load through multimodal physiological data. *Cognition, Technology & Work*, 23(4), 567–585. <https://doi.org/10.1007/s10111-020-00647-6>

Yu, X., Lu, J., Liu, W., Cheng, Z., & Xiao, G. (2024). Exploring physiological stress response evoked by passive translational acceleration in healthy adults: A pilot study utilizing electrodermal activity and heart rate variability measurements. *Scientific Reports*, 14, 11349. <https://doi.org/10.1038/s41598-024-61656-5>

Zeitlhofer, I., Zumbach, J., & Schweppe, J. (2024). Complexity affects performance, cognitive load, and awareness. *Learning and Instruction*, 94, 102001. <https://doi.org/10.1016/j.learninstruc.2024.102001>