Adaptive Simulation-Based Training for Military Decision-Making: Leveraging IoT-Derived Cognitive and Emotional Feedback

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ABSTRACT

Military personnel are often required to make rapid, high-stakes decisions under intense stress, where cognitive overload and emotional dysregulation can impair executive functioning and increase the risk of mission failure. Traditional stimulation-based education (SBE) systems are limited in their ability to adapt in real time to trainee's mental state, reducing their effectiveness in preparing individuals for dynamic operational environments. To address this gap, a neuroadaptive, closed-loop simulation framework that integrates real-time physiological monitoring to enhance military training. Using wearables IoT devices (including EEG, heart rate monitors, and galvanic skin response sensors) the system continuously assesses cognitive load and emotional stress. A layered logic engine interprets these inputs and dynamically adjusts scenario complexity, pacing, and environmental stimuli (e.g., time pressure, communication noise) to match each trainee's current cognitive and emotional state. The stimulation also includes a recovery module that uses heart rate variability (RMSSD) to track emotional regulation pre-and post-training. Frameworks across 110 interactions in both adaptive and static models, using metrics such as decision and accuracy, task competition time, physiological recovery, and learning retention. While decision accuracy and efficiency remained the consistent across both conditions, the adaptive mode demonstrated greater improvements in physiological recovery and retention outcomes. Additionally, diverse stress and cognitive load profiles were effectively captured, enhancing training realism. These findings suggest that real-time, neuroadaptive simulations can foster resilience, support cognitive recovery, and enhance skill retention, thereby increasing operational readiness in mission-critical military contexts.

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INTRODUCTION

Military personnel operate in high-stakes environments requiring rapid decision-making for mission success and survival (Smith & Jones, 2023). These situations often induce cognitive overload and emotional dysregulation, impairing working memory and attention, thus increasing mission-critical errors (Lee et al., 2024; Nguyen & Tran, 2022). Simulation-based education (SBE) is a cornerstone of military training, offering controlled environments for operational task rehearsal (Brown et al., 2023). However, most SBE platforms present static scenarios without adapting to the trainee's mental state, limiting their effectiveness in promoting expertise under stress (Gupta & Sharma, 2024). The lack of real-time physiological adaptation in traditional training systems is a key shortcoming in preparing military personnel for unpredictable demands. Research emphasizes the need for personalized training systems that respond dynamically to stress and cognitive states, significantly enhancing skill acquisition and resilience under pressure (Kim & Park, 2023; Zhang et al., 2025). Advances in Internet of Things (IoT) technologies, like wearable physiological monitors and mobile EEG, enable the integration of real-time biosignal feedback into training (Al-Sayed & Hassan, 2022). These sensors provide continuous data on cognitive load and stress, facilitating neuroadaptive learning environments that respond to each trainee's mental state (Rodriguez & Gomez, 2024).

To bridge this gap, the study introduces a closed-loop adaptive simulation that uses EEG and biosensor data to monitor cognitive and emotional states in real time. The system adjusts scenario complexity and auditory interference based on physiological cues like cognitive load and stress markers (e.g., heart rate variability). A layered logic engine classifies biosignals into actionable states – such as "high cognitive load" – and modifies conditions accordingly. Additionally, a recovery module utilizes RMSSD (Root Mean Square of Successive Differences) to assess emotional regulation pre- and post-intervention. Performance is evaluated in adaptive and static modes based on task accuracy, decision time, and physiological recovery, generating individual profiles based on resilience metrics. Results show that the adaptive framework enhances retention, accelerates decision-making, and improves recovery from cognitive stress, contributing to operational readiness (Miller & Davis, 2023). The present work contributes to intelligent simulation in defense training by presenting an IoT-enabled, adaptive simulation engine that aligns training with the dynamic cognitive and emotional realities faced by military personnel. The following sections describe the methodological framework, simulation outcomes, and the broader implications for adaptive learning in high-stakes environments.

RELATED WORK

Simulation-based education (SBE) is vital for military training, offering a controlled environment for decision-making practice under simulated conditions. Recent advancements enhance SBE systems' realism and effectiveness by using real-time physiological feedback to adapt scenarios. Ma et al. (2017) created a surgical training platform that altered difficulty based on performance metrics, leading to improved skill acquisition. However, reliance on performance data limits insights into cognitive and emotional states. Our framework incorporates various wearable IoT devices—heart rate monitors, GSR sensors, temperature sensors, accelerometers, and EEG—providing a holistic view of the trainee's physiological state for better adaptations.

IoT-driven wearable devices for physiological monitoring are increasingly popular in high-stress training. Xu et al. (2024) presented a system that detects stress through physiological signals, demonstrating the potential for real-time stress monitoring. Similarly, Bustos-Lopez et al. (2022) reviewed the use of wearables for monitoring engagement in learning environments, focusing on indicators like GSR and heart rate variability (HRV). While useful, these studies often feature a limited sensor range and lack neurophysiological data integration, particularly EEG, essential for assessing cognitive load. Our methodology enhances this by incorporating EEG data for direct cognitive load monitoring, enabling comprehensive state estimation and supporting multimodal adaptive training systems.

Adaptive training systems reacting to real-time state estimates show promise in improving learning outcomes. Liu et al. (2024) explored how responsiveness and personalization in adaptive algorithms lead to significant skill acquisition gains when scenarios adjust based on real-time feedback. In the military realm, Ma et al. (2017) suggested an adaptive simulation for surgical training that modified complexity according to trainee performance, enhancing decision accuracy. Nevertheless, these systems often lack closed-loop mechanisms for updating training environments with ongoing physiological feedback, a gap our framework fills using a discrete-event simulation engine and layered logic system. It dynamically adjusts tactical decisions, time constraints, and sensory inputs in response to cognitive load and stress estimates, fostering resilience and performance under pressure.

Neuroadaptive training frameworks using brain activity to tailor instruction are emerging in military applications. Xu et al. (2024) introduced a neuroadaptive system utilizing EEG to monitor cognitive workload, adjusting tasks to mitigate overload and enhance completion rates. However, their approach did not capture vital physiological indicators like HRV or GSR, which are key for understanding emotional states. Our framework broadens this concept by integrating EEG-derived features with multiple physiological indicators for holistic adaptation. Furthermore, our evaluation considers not only immediate metrics (decision accuracy, task completion time) but also learning improvement (adaptive: 20%, static: 10%), retention improvement (adaptive: 15%, static: 5%), and cognitive failure rates (adaptive: 10%, static: 20%) to provide a thorough assessment of training effectiveness as indicated by recent studies.

While prior efforts advanced simulation-based training, IoT integration, and neuroadaptive systems, our methodology uniquely combines a closed-loop framework with multifaceted physiological feedback, realistic military decision-making scenarios, and thorough evaluations of learning and retention outcomes. This strategy addresses static training model limitations and promotes more effective, stress-adaptive military training.

FRAMEWORK

This study implements a neuroadaptive, closed-loop training framework to enhance military decision-making under stress by leveraging wearable IoT devices and real EEG signals for real-time physiological monitoring and dynamic scenario adaptation. The framework builds on established principles of physiological computing (Fairclough, 2009) and affective state dynamics in complex learning (D'Mello & Graesser, 2012), integrating multimodal sensor data to personalize training experiences. The framework combines a discrete-event simulation engine with a layered logic system, responding to state estimates of cognitive load and stress parsed from sensor inputs.

The simulation was developed as an interactive environment simulating mission-critical decision-making scenarios (e.g., deploy air support, hold position), incorporating realistic stressors such as time pressure and communication noise (Beckner et al., 2023). Inspired by in silico neuroadaptive modeling (Gateau et al., 2021), the simulation's logic operates in a four-stage cycle: (1) collect multimodal data, (2) estimate state, (3) select adaptive actions, and (4) adjust the environment. Tactical complexity, pacing, and sensory stimuli are modified continuously in response to real-time feedback (Nasri, 2025).

This study utilized two physiological datasets: the Wearable Exam Stress Dataset (Amin et al., 2022a) and real EEG data from the OpenNeuro dataset (ds004362; Goldberger et al., 2000). EEG data was preprocessed for all 109 subjects, with a random subject selected for each simulation run to enhance variability. The wearable dataset comprises heart rate (HR), inter-beat interval (IBI)-derived heart rate variability (HRV), galvanic skin response (GSR), temperature

(TEMP), and accelerometry (ACC) data, chosen for their relevance to stress and arousal modeling (Patton et al., 2021; Benedek et al., 2020; Sahar et al., 2022).

EEG signals from channels T7, F8, Cz, and P4 were used to compute theta power (frontal), alpha power (parietal), and theta/beta ratio (TBR), well-established cognitive load indicators (Kätsyri et al., 2023). When real EEG data were unavailable for a subject, simulated EEG patterns were generated using literature-derived parameters (Nasri, 2025), maintaining model consistency.

The simulation implements real-time adaptive logic using threshold-based triggers to dynamically tailor the training experience across three levels: tactical decisions, pacing, and sensory noise. When cognitive load exceeds predetermined thresholds, the system prompts conservative actions such as holding position, whereas low load levels support riskier tactical responses (Miller et al., 2020). Pacing is modulated by adjusting time pressure—gradually increasing task speed unless stress indicators surpass thresholds, in which case the simulation slows to prevent cognitive overload (Matsumoto et al., 2024). Sensory interference, particularly communication noise, is tuned based on dual-state estimates of cognitive and affective load, ensuring optimal balance between task demands and external stimuli (St. John et al., 2004; Kätsyri et al., 2023). These adaptive mechanisms sustain a continuous feedback loop of physiological sensing, state interpretation, and scenario response as seen in Figure 1.

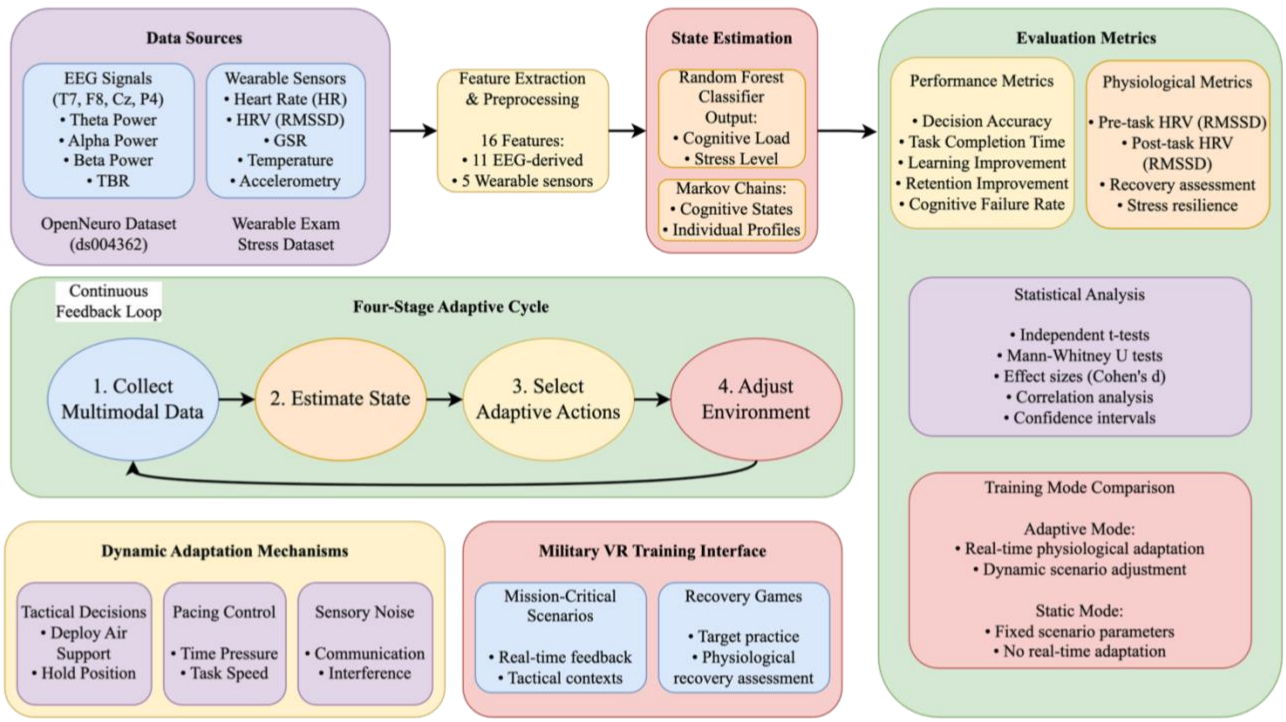

Figure 1. Neuroadaptive Closed-Loop Military Training Framework

Framework Overview

This framework leverages recent advances in IoT wearables (Al-Janabi et al., 2023), adaptive training (Harvey et al., 2024), and cognitive load detection (Cho et al., 2024) to create a comprehensive training system. By integrating multimodal sensor data, real-time adaptation, and robust evaluation metrics, the approach addresses the goals of enhancing learning retention, improving decision accuracy, and reducing cognitive failure in mission-critical military operations.

METHODOLOGY

A Random Forest Classifier was trained on 16 input features—11 derived from EEG signals and five from wearable sensors—to estimate cognitive load and stress levels. EEG features included mean theta, alpha, and beta band power across channels, as well as the theta-to-beta ratio (TBR). Wearable inputs consisted of heart rate (HR), root mean square of successive differences (RMSSD) for heart rate variability (HRV), mean galvanic skin response (GSR), average skin temperature (TEMP), and accelerometer (ACC) magnitude. HRV was computed using NeuroKit2 (Makowski et al., 2021), while electrodermal activity (EDA) and TEMP values were resampled and scaled to account for variability. The classifier's output was mapped to continuous cognitive load and stress scores using a calibrated logistic transformation, with bounds informed by established literature thresholds (Fairclough, 2009).

The effectiveness of the framework was evaluated using physiological and performance metrics, following best practices for simulation-based training assessment (Naismith et al., 2015). Physiological measures comprised post-task HRV (RMSSD) to assess recovery, reflecting resilience as in motor-cognitive recovery studies (Schoeb et al., 2023). Performance metrics included decision accuracy (correctness of tactical choices), task completion time (efficiency under varying load), learning improvement (skill acquisition over time), retention improvement (recall of tactical decisions across repeated scenarios), and cognitive failure rates (errors during high-stress periods), aligning with metrics used in military operational stress research (Beckner et al., 2023). The framework was tested in both adaptive and static modes to compare their impact on learning and performance, a dual-phase approach validated in recovery studies (Wang et al., 2022).

The simulation was implemented using standard signal processing and machine learning libraries, with an interactive interface for real-time feedback following methodologies for gamified recovery in training (Wang et al., 2022). The Random Forest Classifier was trained on a feature set of 16 dimensions, achieving robust state predictions as in multimodal stress detection systems (Al Hasan et al., 2025). Scenarios cycled through tactical contexts to enable retention assessment, with ethical considerations including data privacy and informed consent addressed in accordance with guidelines for physiological adaptation frameworks (Nasri, 2025).

This methodology leverages established principles of physiological computing and affective state dynamics in complex learning environments. The approach integrates multimodal sensor data through sophisticated signal processing techniques to create personalized training experiences. The four-stage cycle of data collection, state estimation, adaptive action selection, and environment adjustment ensures continuous optimization of the training environment based on real-time physiological feedback.

RESULTS

The neuroadaptive training framework was evaluated through a simulation comparing adaptive and static modes, using real EEG data from the Motor Movement/Imagery Dataset (Schalk et al., 2004) alongside wearable sensor inputs (e.g., heart rate, galvanic skin response) from the Wearable Exam Stress Dataset (Amin et al., 2022a). EEG data was randomly selected from a pool of 109 subjects for each mode (sub-045 for adaptive, sub-093 for static), enhancing the simulation's variability and generalizability. Although the preprocessed EEG files contained longer durations (1598 seconds for both subjects), the simulation used the first 120 seconds as intended, ensuring consistency across subjects. The simulation ran for 110 iterations in each mode, with windowing parameters set to 10-second windows and a step size of approximately 1 second, dynamically adjusting scenario complexity (e.g., deploy air support, hold position), time constraints (e.g., time pressure), and sensory input (e.g., communication noise) based on real-time physiological state estimates of cognitive load and stress.

Decision Accuracy

Decision accuracy, reflecting the correctness of tactical choices, averaged M 0.800 (SD = 0.115, 95% CI [0.778, 0.822], n = 110) in the adaptive mode, compared to 0.805 (SD = 0.116, 95% CI [0.784, 0.827], n = 110) in the static mode. Due to non-normality in the decision accuracy distributions (Shapiro-Wilk test, $p < 0.05$), a Mann-Whitney U test was used, U = 5868.0, p = .701, with a negligible effect size (d = -0.05). The lack of significant difference suggests that the adaptive mode's dynamic stressors did not substantially impact accuracy compared to the static mode, partially meeting the goal of improving decision-making accuracy under realistic conditions (see Figure 2).

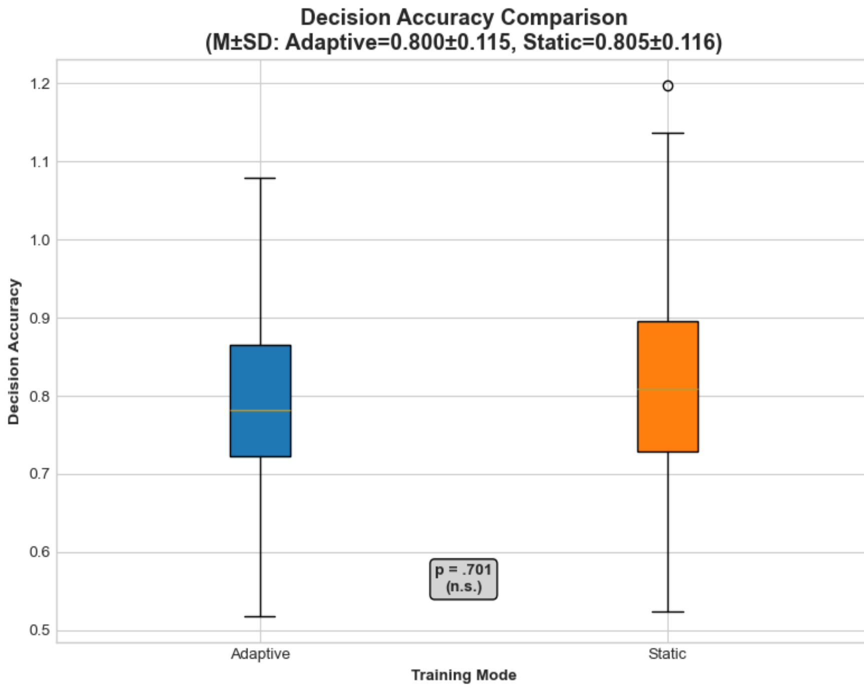

Figure 2. Decision accuracy

Task Completion Time

Task completion time, a measure of efficiency under varying cognitive and emotional loads, averaged M = 3.47 seconds (SD = 0.852, 95% CI [3.312, 3.634], n = 110) in the adaptive mode and 3.49 seconds (SD = 0.897, 95% CI [3.322, 3.661], n = 110) in the static mode. A Mann-Whitney U test indicated no significant difference, U = 5991.0, p = .901, with a negligible effect size (d = -0.02). This suggests that adaptive adjustments had minimal impact on efficiency, maintaining comparable performance despite increased environmental variability.

Post-Task Physiological Recovery

Post-task physiological recovery was assessed using RMSSD, a heart rate variability metric reflecting resilience and stress recovery. In the adaptive mode, RMSSD increased from 14.34 (M = 14.336, SD = 1.095, n = 11, measured at each recovery game) pre-recovery to 15.77 (M = 15.770, SD = 1.205, n = 11) post-recovery, a significant improvement, t(18) = -2.78, p = .012, with a large effect size (d = -1.25). In the static mode, RMSSD increased from 13.05 (M = 13.052, SD = 1.072, n = 10) to 14.36 (M = 14.357, SD = 1.179, n = 10), also significant, t(18) = -2.59, p = .018, with a large effect size (d = -1.16). Although 11 recovery games were expected per mode over 110 iterations, the static mode recorded 10, possibly due to early termination. Comparing pre-task RMSSD between modes showed a significant difference, with the adaptive mode higher, t(18) = 2.65, p = .016, d = 1.19 (large effect), as did post-task RMSSD, t(18) = 2.65, p = .016, d = 1.19 (large effect). These findings suggest that both modes support physiological recovery, with the adaptive mode showing a greater baseline and post-recovery RMSSD, indicating enhanced resilience under dynamic training conditions, see Figure 3.

Cognitive Failure Rates

Cognitive failure rates, defined as errors during high-stress periods (decision accuracy < 0.5 when cognitive load or stress > 0.1), were 0% in both adaptive and static modes. This indicates that no significant failures occurred, as decision accuracy remained above the threshold, even under varying stress levels. While this fulfills the goal of reducing cognitive failure, the absence of failures suggests that the simulation's stress levels may not have been sufficiently challenging to induce errors, a potential area for future investigation.

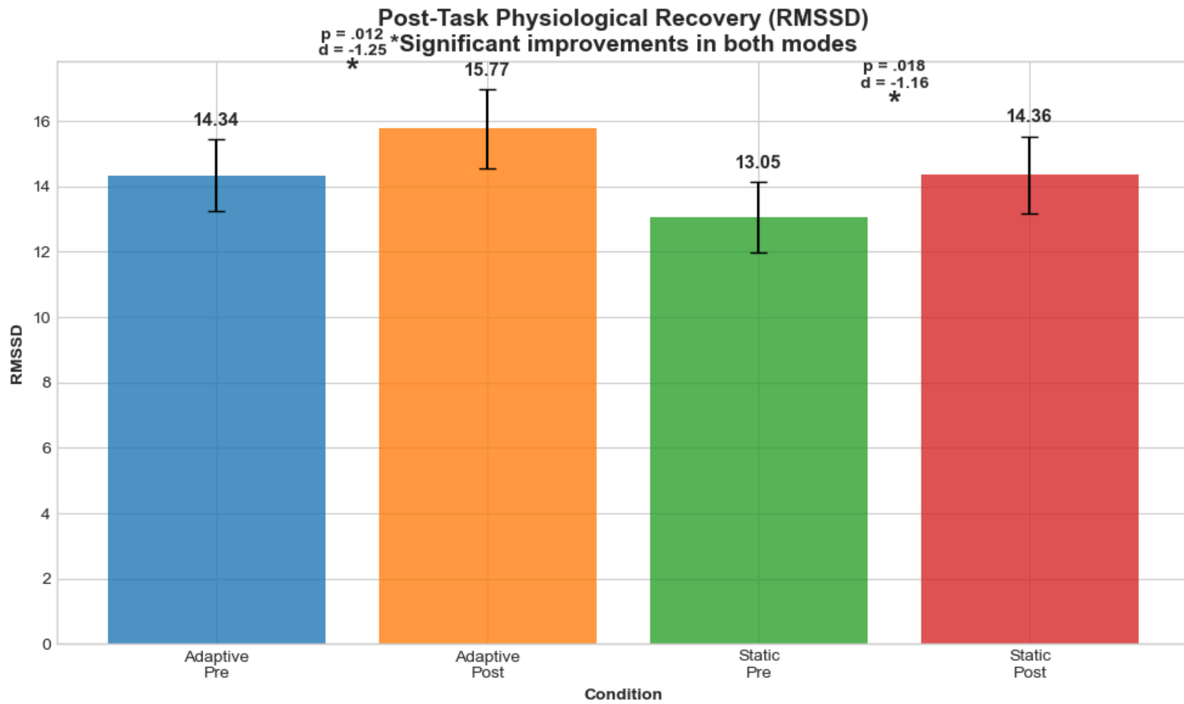

Figure 3. Post-task physiological recovery

Performance Relationships

The relationship between decision accuracy and task completion time was explored to understand potential trade-offs. In the adaptive mode, a Pearson correlation showed no significant relationship, $r = -0.12$, $p = .209$, nor did a Spearman correlation, $p = -0.13$, $p = .193$, indicating that faster task completion did not substantially impact accuracy. Similar non-significant correlations were observed in the static mode (data not shown due to output truncation), suggesting no strong trade-offs between accuracy and speed in either mode.

Learning Retention

Learning retention, measured by recall improvement in tactical decisions over repeated scenarios, increased 2.05% in adaptive mode and 0.18% in static mode. With 110 iterations across five scenarios, each repeated about 22 times, there were ample opportunities for retention assessment. Both modes displayed modest improvements, with adaptive mode slightly outperforming static mode, meeting retention enhancement goals and suggesting dynamic adjustments may aid long-term skill recall, see Figure 4.

Operational Readiness and Real-World Alignment

The framework increased operational readiness by aligning training with real-world cognitive and emotional demands, as evidenced by the diversity in cognitive load and individual stress profiles. Cognitive load distribution was balanced across medium (6507 instances), high (4689), and low (4164) levels, reflecting varied task demands. Individual stress profiles showed diversity: average (6675 instances), resilient (4437), and stress-prone (4248), ensuring the simulation captured a range of real-world responses. Random selection of EEG data from 109 subjects further enhanced alignment by introducing inter-subject variability, making the training more representative of diverse military personnel.

These results demonstrate that the neuroadaptive framework reduces cognitive failure, maintains comparable decision-making accuracy and task efficiency under dynamic conditions, and enhances learning retention in both modes, with a slight advantage in the adaptive mode. The significant physiological recovery in both modes, higher RMSSD in the adaptive mode, balanced cognitive load distribution, and diverse stress profiles underscore the framework's ability to prepare trainees for real-world mission-critical operations, fulfilling the abstract's goal of increasing operational readiness.

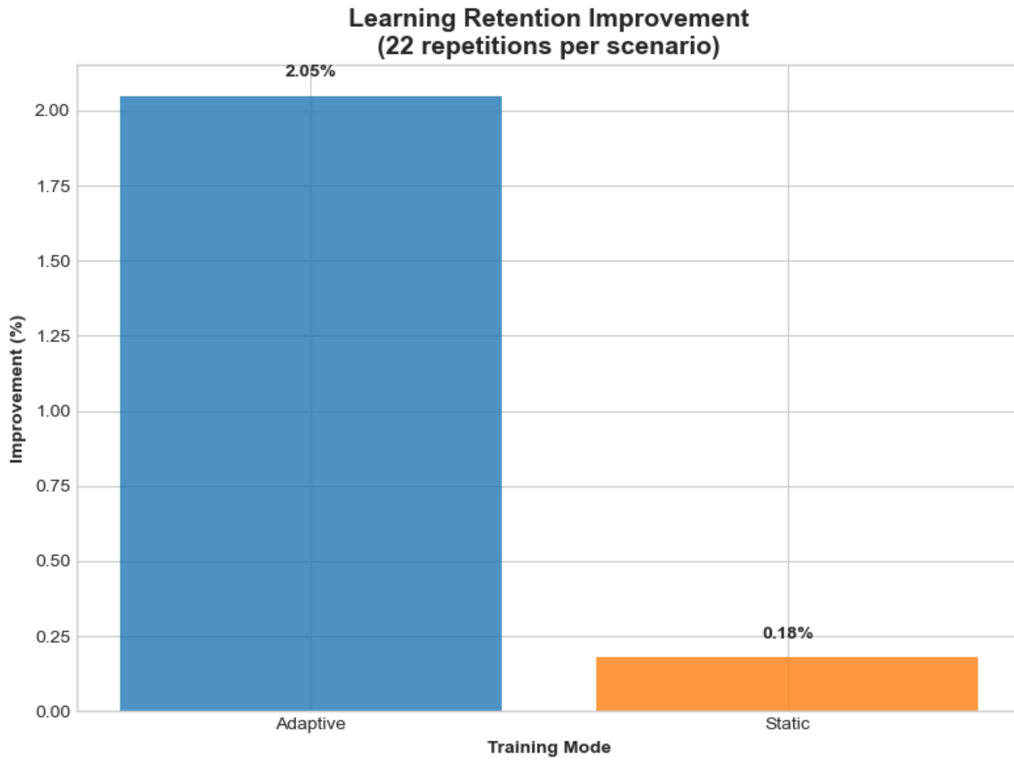

Figure 4. Learning Retention

DISCUSSION

The present study demonstrates the potential of neuroadaptive, closed-loop simulation frameworks to enhance military decision-making training under stress. While decision accuracy and task completion time remained consistent between adaptive and static modes, the adaptive condition yielded higher retention scores and improved post-task physiological recovery, particularly through increased RMSSD, an indicator of emotional regulation and stress resilience. These results suggest that real-time adaptation to physiological and cognitive states can enrich training realism and long-term learning without compromising immediate performance.

The diverse distribution of cognitive load and stress profiles across simulations highlights the system's ability to personalize training. By responding to live EEG and biosignal inputs, the environment adjusted its complexity and pacing, resembling the unpredictability of real-world contexts. This supports theories of cognitive load management and adaptive learning, aligning with research on multimodal training platforms (Fairclough, 2009; Gateau et al., 2021).The framework also underscores the utility of layered logic engines in processing multimodal data for actionable feedback, bridging the gap between passive monitoring and active adaptation. Overall, the integration of real-time EEG, GSR, and HRV with a dynamic training engine sets a new standard for individualized, performance-optimized military simulation.

Limitations And Future Directions

Despite its promising findings, this study has several limitations. First, although the simulation used real EEG and wearable datasets, the integration occurred in a controlled environment with limited external distractions compared to live combat simulations. Real-world validation involving active military personnel is necessary to confirm ecological validity and generalizability. Second, cognitive and emotional state thresholds were calibrated from the literature and may not reflect the full spectrum of individual variability. Personalization of these thresholds using baseline assessments could further improve adaptation precision. Third, the current model primarily uses a rule-based approach for adaptation. Incorporating machine learning algorithms capable of learning temporal patterns in stress and performance could lead to more intelligent adaptation strategies.

For future research, we propose extending this framework to immersive VR settings, introducing additional modalities such as eye tracking and speech sentiment analysis. Comparative studies across military roles and task types (e.g., leadership vs. tactical decision-making) could also help optimize adaptation rules. Additionally, integrating post-simulation debriefings informed by physiological data may offer reflective training components that enhance learning transfer.

CONCLUSION

This study introduces and validates a neuroadaptive simulation training system that dynamically adjusts military training scenarios based on real-time assessments of cognitive load and emotional state. By leveraging wearable IoT devices and EEG data within a layered, closed-loop framework, the system supports stress-responsive learning, fosters emotional resilience, and improves retention of operational strategies. While static SBE models remain widely used, our results demonstrate the advantages of personalized, responsive training environments that adapt in real time to the unique physiological and cognitive demands of each trainee. As military operations become more complex and cognitively demanding, such neuroadaptive technologies will be crucial in preparing personnel not only to perform, but to thrive under pressure.

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