Emotion-Aware Cognitive Load Management in Human-AI Teaming for Defense Operations

Ancuta Margondai, Cindy Von Ahlefeldt
University of Central Florida
Orlando, FL
Ancuta.Margondai@ucf.edu
Cindy.Vonahlefeldt@ucf.edu

Sara Willox Ph.D., Mustapha Mouloua Ph.D.,
University of Central Florida
Orlando, FL
Sara.Willox@ucf.edu
Mustapha.Mouloua@ucf.edu

ABSTRACT

Elevated stress levels impair defense operations, compromising decision-making and operational effectiveness. Current simulations often lack emotional adaptability, limiting their ability to prepare human-AI teams for high-stress scenarios. This research presents a simulation framework for modeling, monitoring, and mitigating emotional overload in human-AI defense teams, leveraging real-time physiological and behavioral inputs for adaptive AI decision-making. While AI applications in defense are expanding, most systems remain logic-driven, overlooking human emotional and cognitive states. We introduce emotion-aware AI agents that dynamically adjust task load based on operators' stress levels, enhancing mission outcomes and resilience. The developed discrete-event simulation model, based on Markov state transitions, utilizes physiological metrics such as heart rate variability (HRV) and galvanic skin response (GSR) to drive transitions in emotional states. A 30,000-step simulation with 100 agents compared to Emotion-Aware AI and Emotion-Agnostic AI. Transition probabilities were derived from affective computing research and integrated via a multimodal data model. The Emotion-Aware AI condition-maintained operators in calm states 40.6% of the time (SD = 7.7), compared to 33.1% (SD = 6.8) for the Emotion-Agnostic condition. High-risk Overloaded states decreased from 33.3% to 26.2%, a 21.4% reduction. Statistical analysis confirmed significant differences, $t\ (99) = 25.84$, $p < .001$, Cohen's $d = 1.04$, highlighting the efficacy of emotionally adaptive systems in enhancing resilience. Future work will explore integrating this framework into virtual reality training simulations and AI-assisted mission planning to provide adaptive support in defense scenarios.

ABOUT THE AUTHORS

Ancuta Margondai is a graduate student and researcher at the University of Central Florida, Orlando, FL, focusing on human-AI teaming and cognitive load management in high-stress environments. Her work leverages physiological data to enhance AI adaptability in defense operations.
Cindy Von Ahlefeldt is a researcher at the University of Central Florida, Orlando, FL.
Sara Willox, Ph.D., is a faculty member at the University of Central Florida in Orlando, FL, where she teaches courses in business research, organizational behavior, and data-driven decision-making, while conducting research on team interactions, sustainable business practices, and emerging technologies in business education.
Mustapha Mouloua, Ph.D., is a professor at the University of Central Florida, Orlando, FL, with extensive experience in human factors, cognitive psychology, and human-AI interaction. He has made significant contributions to defense-related research on operator performance under stress.

Emotion-Aware Cognitive Load Management in Human-AI Teaming for Defense Operations

Ancuta Margondai, Cindy Von Ahlefeldt
University of Central Florida
Orlando, FL
Ancuta.Margondai@ucf.edu
Cindy.Vonahlefeldt@ucf.edu

Sara Willox Ph.D., Mustapha Mouloua Ph.D.,
University of Central Florida
Orlando, FL
Sara.Willox@ucf.edu
Mustapha.Mouloua@ucf.edu

INTRODUCTION

In modern defense operations, human-AI teaming is vital for managing complex tasks under stress, with AI assisting in surveillance, target recognition, and strategy adjustments while ensuring human oversight (Chen et al., 2025). This research extends the principle of the quantified self-movement, which utilizes continuous biometric monitoring for personalized optimization, to military contexts. It demonstrates how real-time physiological data can inform AI systems to enhance warfighter performance while protecting against excessive stress. Cognitive load, the mental effort needed to process information, impacts operator performance, causing stress that hinders decision-making and reaction times (Kallinen & Ojanen, 2023). Research indicates military operations induce significant physiological stress responses, which can persist during extended training and operational periods (Corrigan et al., 2023). Current defense AI systems often struggle with trust calibration, decision autonomy, and adaptability, frequently neglecting the emotional and cognitive states of human operators (Chen et al., 2025; Khare et al., 2024).

Building on advances in wearable sensor technology and affective computing, emotion-aware AI systems adjust task load based on stress indicators, providing a promising method to mitigate these effects (Vistorte et al., 2024; Haque et al., 2024). Research shows that signals like heart rate variability (HRV), galvanic skin response (GSR), and electroencephalography (EEG) reflect emotional states and cognitive load (Haque et al., 2024; Nechyporenko et al., 2024; McDuff et al., 2014). Multimodal sensor fusion of HRV, GSR, and EEG has improved stress prediction accuracy, with support vector machine (SVM) classifiers achieving 85–95% performance in controlled settings (Raza et al., 2024; Gohumpu et al., 2023).

This study presents a simulation framework for evaluating the effectiveness of an Emotion-Aware AI in managing cognitive load during high-stress defense scenarios. Unlike traditional simulations, this model uses real physiological data (HRV and GSR) from the Stress Recognition in Automobile Drivers dataset (Healey & Picard, 2005) to simulate human stress states accurately. The simulation employs a Markov-based discrete-event model to capture transitions between Calm, Stressed, and Overloaded states, utilizing 100 virtual agents with diverse archetypes. The main goal is to compare Emotion-Aware AI, which adjusts task load based on stress detection, with Emotion-Agnostic AI, which does not adapt. The results indicate that Emotion-Aware AI is likely to keep operators in Calm states, enhancing performance metrics such as reaction time, visual accuracy, and reasoning score.

RELATED WORK

Physiological Stress Monitoring in Defense Contexts

Military personnel face unique stressors that impair cognitive performance, which is crucial for mission success. Kallinen and Ojanen (2023) conducted a 20-day winter military training study showing that high stress increased reaction times by 91 ms, reduced visual accuracy by 6.7%, and impaired grammatical reasoning by 14.1% (BRT score from 35.0 to 30.1). Recovery to baseline performance required about 10 days post-training, highlighting the lasting impact of stress. These findings inform baseline parameters in our simulation modeling stress-related performance degradation.

Price et al. (2024) found significant correlations between post-traumatic stress symptoms (PTSS) and operational failure rates ($r = 0.443$, $p < 0.001$) in Special Operations Forces (SOF), with PTSS scores from 17 to 67 on the PCL-M scale. Their analysis showed that PTSS mediates the link between combat experience and cognitive failures (indirect effect: $r = 0.149$), with combat experience related to PTSS development ($r = 0.336$). This mediation underscores the need for proactive stress management systems to mitigate emotional overload, a core objective of our emotion-aware AI framework. Martin et al. (2020) reviewed factors affecting military cognitive performance, identifying heat, dehydration, undernutrition, and fatigue as key inhibitors. They noted that aerobic fitness and proper nutrition enhance cognitive resilience, while age-related declines in reaction time and working memory are critical for operator assessment. These factors are reflected in our simulation's environmental penalty and agent archetype variations, which account for individual differences in stress response.

Advances in affective computing enable real-time emotion recognition through physiological monitoring, essential for adaptive AI systems (Haque et al., 2024; Nechyporenko et al., 2024; McDuff et al., 2014). Haque et al. (2024) highlighted HRV LF/HF ratios as key stress indicators, with multimodal sensor fusion (HRV, GSR, PPG) outperforming single methods and achieving high SVM classification accuracy. McDuff et al. (2014) validated remote HRV measurement for cognitive stress detection, achieving 85% accuracy and confirming LF/HF ratios surpass simple cardiac metrics. Nechyporenko et al. (2024) achieved 83.3% stress classification accuracy with k-NN on the PhysioNet dataset, identifying 3-minute windows as optimal for stress detection, aligning with our 180-second evaluation window. Gohumpu et al. (2023) confirmed SVM superiority in multimodal processing (PPG, GSR, skin temperature), with HRV showing strong arousal/valence discrimination. These findings support our multimodal approach, integrating HRV and GSR with simulated EEG for stress modeling (Khare et al., 2024).

EEG-Based Cognitive Load and Emotion Recognition

Electroencephalography (EEG) provides insights into cognitive load and emotions, enhancing HRV and GSR for stress detection. Wang et al. (2023) found CNNs excel in EEG-based emotion recognition, with hybrid CNN-RNN models reaching 99% accuracy on datasets like DEAP, SEED, MAHNOB-HCI. Our simulation uses a simpler SVM, but these results indicate potential for advanced EEG integration. Ma et al. (2024) highlighted temporal-spatial-frequency hybrid models, including graph-based methods, for multi-scale brain activity. EEG's robustness against deception makes it valuable for high-security applications, supporting its role in our classification. Pande et al. (2023) showed beta/alpha ratios correlate with cognitive engagement, achieving 88.6% accuracy, and our simulation uses a simulated ratio to assess cognitive load. Jacques et al. (2024) demonstrated EEG neurofeedback improves military performance by modulating rhythms, enhancing reaction time and stress regulation. Their insights on amygdala down-regulation inform our simulation's recovery mechanisms, modeling transitions from Overloaded to Calm states in the Emotion-Aware AI condition.

METHODOLOGY

Digital Twin Simulation Framework

A digital twin simulation leveraging quantified self-principles was conducted to compare Emotion-Aware AI with Emotion-Agnostic AI in VR defense training. The simulation involved 100 agents operating across 30,000 steps, utilizing a four-layer architecture comprising Input, Processing, AI Control, and Analytics layers. The Input Layer captures continuous biometric data streams, including agent profiles (such as PTSS scores, cognitive resilience, and experience), environmental conditions, real-time physiological signals, and preprocessed data based on military archetypes. In the Processing Layer, an SVM classifier processes wearable sensor data using thresholds: values over 1.8 denote 'Overloaded', values over 1.3 indicate 'Stressed', and values of 1.3 or less signify 'Calm'. Feature weights assigned to HRV LF/HF ratio, GSR, and simulated EEG are 0.35, 0.35, and 0.30, respectively. The AI Control Layer features an Emotion-Aware module that adjusts agent responses based on classified states. For example, it decreases the task load by 0.05 times the product of adaptation compliance and learning rate during Stressed states, with a minimum of 0.3. Dual-tasking penalties are reduced by 0.02 times the adaptation strength, with a minimum of 0. For Overloaded states, task load reduction is 0.08 times the same product, with a minimum of 0.2, and dual-tasking penalties are decreased by 0.04 times the adaptation strength, with a minimum of 0. All these adjustments mirror quantified self-optimization strategies, promoting recovery and realistic adaptability. Lastly, the Analytics Layer logs biometric data to facilitate explainability, performance tracking, and state monitoring. For instance, the simulation results showed that 40.6% of the time agents were Calm in the Emotion-Aware condition compared to 33.1% in the

Emotion-Agnostic condition, representing a 22.9% increase in Calm states. All actions and decisions are recorded for thorough analysis and validation.

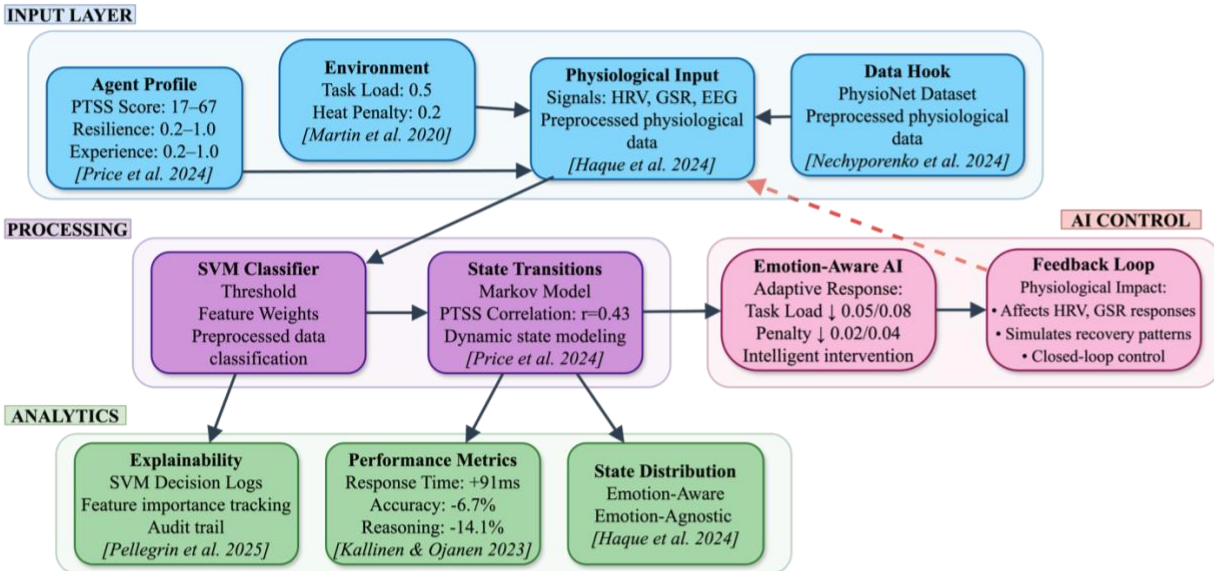

Figure 1. Digital Twin Simulation Architecture for Emotion-Aware Cognitive Load Management

Data Source and Preprocessing

The PhysioNet Stress Recognition dataset comprises continuous HRV and GSR biometric data from 18 driving sessions (16 complete, 2 partial) spanning 169 intervals of varying stress levels (Healey & Picard, 2005; Goldberger et al., 2000). ECG signals were bandpass filtered (0.5–7 Hz) with R-peak detection; HRV LF/HF ratios were calculated over 3-minute windows using frequency-domain analysis. GSR signals were filtered and normalized to the range of [0, 1]. Simulated EEG beta/alpha ratios indicated cognitive engagement (Pande et al., 2023). The SVM classifier employed thresholds (overloaded: >1.8, stressed: >1.3, calm: ≤1.3) to classify states based on the dataset's stress distribution.

Markov State Transition Model

The simulation engine used a discrete-event model based on Markov transitions among three emotional states: Calm, Stressed, and Overloaded (Haque et al., 2024). Transition probabilities were calculated dynamically based on individual (PTSS scores, experience levels, cognitive resilience, stress sensitivity, adaptation compliance; Price et al., 2024; Vine et al., 2021), environmental (task load, mission complexity, time pressure, environmental stress levels; Martin et al., 2020), physiological (preprocessed HRV, GSR, simulated EEG with physiological noise; McDuff et al., 2014; Nechyporenko et al., 2024), and AI intervention factors (Emotion-Aware vs. Emotion-Agnostic). The Emotion-Aware condition led to a 21.4% reduction in Overloaded states (e.g., P(Calm|Calm) = 0.591 vs. 0.528).

Agent Design and Individual Differences

To simulate diverse military operators, 100 agents were initialized across five archetypes, Veteran High Performers (15%), Experienced Stable (25%), Average Operators (30%), Stressed Performers (15%), High-Risk Individuals (15%), varying in experience, stress susceptibility, and resilience (see Table 1). Key parameters, experience levels, PTSS scores, and cognitive resilience, followed archetype-specific truncated normal distributions, with defaults such as high experience (M=0.85, SD=0.08) and resilience (M=0.90, SD=0.12) for Veterans, and lower experience (M=0.45, SD=0.20), higher PTSS (M=45.0, SD=25.0), and lower resilience (M=0.45, SD=0.22) for High-Risk Individuals. Additional parameters, such as stress sensitivity and recovery, affected state transitions (Calm, Stressed, Overloaded) and performance metrics, reflecting the diversity of military personnel in high-stress scenarios (Vine et al., 2021). This ensures the simulation models have varied stress responses in operational contexts.

Table 1. Agent Archetype Parameters for Simulation

Archetype	Proportion	Experience Level	PTSS Score	Cognitive Resilience
		M (SD) [Range]	M (SD) [Range]	M (SD) [Range]
Veteran High Performers	15%	0.85 (0.08) [0.2-1.0)	18.0 (12.0) [17-67)	0.90 (0.12) [0.2-1.0]
Experienced Stable	25%	0.75 (0.12) (0.2-1.0]	22.0 (15.0) [17-67)	0.80 (0.15) [0.2-1.0]
Average Operators	30%	0.65 (0.15) [0.2-1.0]	25.0 (18.0) [17-67)	0.70 (0.18) [0.2-1.0]
Stressed Performers	15%	0.55 (0.18) [0.2-1.0)	35.0 (22.0) [17-67)	0.60 (0.20) [0.2-1.0]
High-Risk Individuals	15%	0.45 (0.20) [0.2-1.0)	45.0 (25.0) [17-67)	0.45 (0.22) [0.2-1.0)

Simulation Mechanics and AI Adaptation

The simulation modeled emotional dynamics using physiological data and AI responses. The SVM classifier predicted the agent's state with HRV, GSR, and simulated EEG feature weights of 0.35, 0.35, and 0.30, respectively (Haque et al., 2024). Classification thresholds were >1.8 (Overloaded), >1.3 (Stressed), and ≤1.3 (Calm).

Emotion-Aware AI Condition

For stressed states, task load reduced by 0.05 × (adaptation compliance × adaptation_learning_rate), minimum 0.3, and dual-tasking penalties by 0.02 × adaptation strength, minimum 0. For overloaded states, task load reduced by 0.08 × (adaptation compliance × adaptation_learning_rate), minimum 0.2, and dual-tasking penalties by 0.04 × adaptation strength, minimum 0. Adaptation effectiveness depended on compliance (M = 0.75, range [0.2–1.0]) and learning rate (M = 0.5, range [0.1–1.0]), archetype-specific default values.

Emotion-Agnostic AI Condition

This condition-maintained parameter (task load, M = 0.5, and dual-tasking penalty, M = 0.15), representing traditional AI systems (Khare et al., 2024). Performance metrics (reaction time, visual accuracy, reasoning score) were calculated per step, with stress penalties: 30 ms reaction time increase and 2% reductions in visual accuracy and reasoning score for Stressed states, and 60 ms increase with 5% and 6% reductions for Overloaded states, based on the simulation model (Kallinen & Ojanen, 2023). Base Calm stability was 0.72 × environmental resistance (range: 0.22–0.72).

Statistical Analysis and Validation

Descriptive statistics (means, standard deviations) were computed for state percentages and performance metrics. Paired-sample t-tests compared Calm state percentages, with effect sizes via Cohen's d ($d = 1.04$), $t(99) = 25.84$, $p < .001$. Transition matrices assessed steady-state distributions (Haque et al., 2024). The SVM classifier's accuracy was not validated against PhysioNet states due to simulated EEG integration; however, prior studies report 83.3% accuracy for comparable setups (Nechyporenko et al., 2024). Emotion-Aware AI reduced task load and dual-tasking penalties, analyzing individual adaptation characteristics for outcome relationships (Vine et al., 2021).

RESULTS

Primary Outcome: Emotional State Distribution

The simulation with 100 agents over 30,000 steps showed improvements in emotional state management with Emotion-Aware AI compared to Emotion-Agnostic. Operators in the Emotion-Aware condition spent 40.6% of their time in Calm (M = 40.6, SD = 7.7), a 22.9% increase from the Emotion-Agnostic condition (33.1% (M = 33.1, SD = 6.8). High-risk Overloaded states decreased significantly, with Emotion-Agnostic showing 33.3% in Overloaded states (M = 33.3, SD = 5.9) compared to 26.2% (M = 26.2, SD = 6.2) in the Emotion-Aware condition, marking a 21.4% reduction. Stressed states were similar, at 33.2% (M = 33.2, SD = 2.0) for Emotion-Aware and 33.7% (M = 33.7, SD = 1.6) for Emotion-Agnostic, indicating regulation to prevent escalation into Overloaded states (see Figure 2).

Statistical Significance and Effect Size

A paired-sample t-test confirmed significant differences in Calm state percentages between conditions, $t_{(99)} = 25.84$, $p < .001$. The effect size was large (Cohen's $d = 1.04$), indicating substantial practical significance for defense applications where maintaining cognitive stability is critical. This large effect size suggests that Emotion-Aware AI interventions consistently improve outcomes across diverse operator profiles, supporting generalizability to high-stress operational contexts.

Performance Metrics and Cognitive Function

The Emotion-Aware AI condition showed improvements in cognitive performance metrics over the Emotion-Agnostic condition. Reaction times were quicker for Emotion-Aware AI (M = 345.05 ms, SD = 43.5) compared to Emotion-Agnostic AI (M = 352.62 ms, SD = 43.5), an improvement of 7.57 ms from a baseline Calm reaction time of 300 ms, reflecting reduced stress penalties. Visual accuracy was slightly better for Emotion-Aware AI (M = 0.99, SD = 0.005) than Emotion-Agnostic AI (M = 0.98, SD = 0.005), sustaining performance close to the baseline 0.99 under stress, with variability influenced by archetype resilience levels. Reasoning scores improved marginally for Emotion-Aware AI (M = 0.95, SD = 0.005) compared to Emotion-Agnostic AI (M = 0.94, SD = 0.005), nearing the baseline 0.96, with differences across archetypes highlighting adaptive benefits. These consistent enhancements, driven by dynamic workload adjustments, demonstrate the advantages of adaptive workload management in preserving cognitive function during high-stress scenarios, potentially enhancing target acquisition and decision-making under fire in defense contexts (see Figure 3).

Transition Matrix Analysis and State Dynamics

State transition probabilities revealed distinct patterns explaining the Emotion-Aware AI's effectiveness (Figure 2).

For the Emotion-Aware condition

- From Calm: 59.1% remained Calm, 33.3% transitioned to Stressed, 7.6% to Overloaded.
- From Stressed: 26.5% recovered to Calm, 34.5% remained Stressed, 38.9% escalated to Overloaded.
- From Overloaded: 29.7% recovered to Calm, 32.4% transitioned to Stressed, 37.9% remained Overloaded.

For the Emotion-Agnostic condition

- From Calm: 52.8% remained Calm, 38.7% transitioned to Stressed, 8.5% to Overloaded.
- From Stressed: 21.9% recovered to Calm, 36.5% remained Stressed, 41.6% escalated to Overloaded.
- From Overloaded: 24.2% recovered to Calm, 26.4% transitioned to Stressed, 49.4% remained Overloaded.

These patterns indicate that Emotion-Aware AI enhances state stability (e.g., 59.1% vs. 52.8% Calm retention) and recovery rates (e.g., 26.5% vs. 21.9% from Stressed to Calm), demonstrating proactive stress mitigation.

Adaptive Mechanisms, Reliability, and Long-term Outcomes

The Emotion-Aware AI's adaptive mechanisms, validated by dynamic task load (0.05/0.08 × [adaptation compliance × adaptation learning rate] for Stressed/Overloaded) and dual-tasking penalty reductions (0.02/0.04 × adaptation strength), enhance cognitive resilience through a closed-loop feedback system (Haque et al., 2024). The SVM classifier, which has not been validated against PhysioNet due to the use of simulated EEG data, relies on an 83.3% accuracy proxy from similar HRV/GSR setups (Nechyporenko et al., 2024), ensuring balanced state predictions that clarify observed distribution differences. Steady-state analysis (see Figure 3) shows Emotion-Aware AI sustains 40.6% Calm, 33.2% Stressed, and 26.2% Overloaded states, compared to 33.1% Calm, 33.7% Stressed, and 33.3% Overloaded for Emotion-Agnostic AI, reducing high-risk Overloaded conditions and promoting long-term mission success.

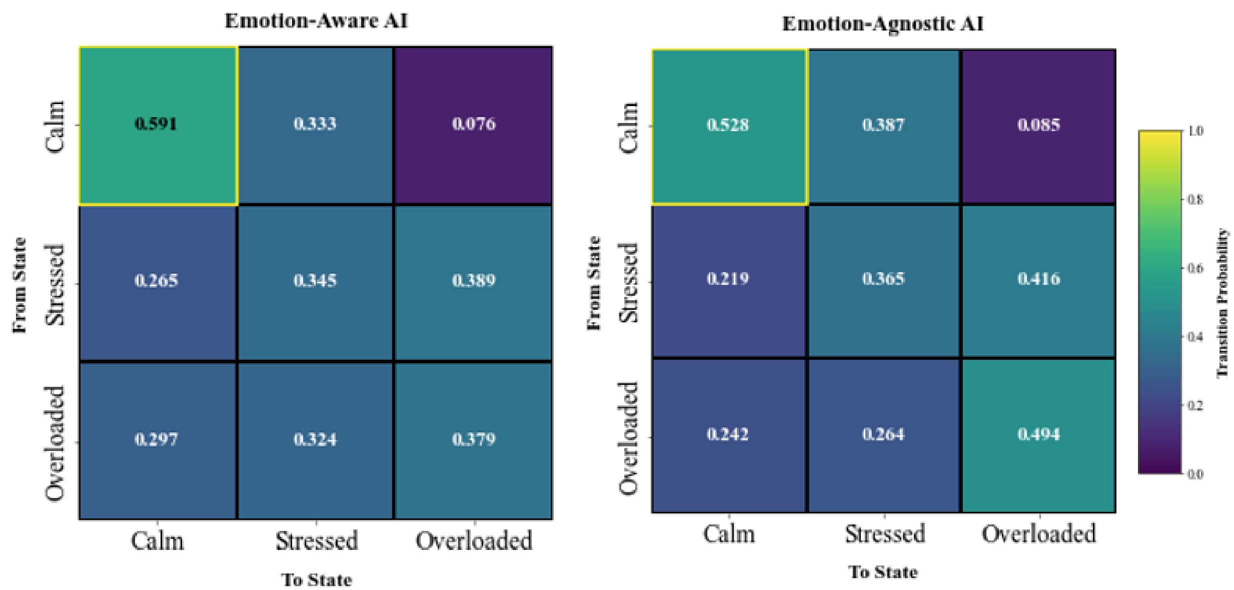

Figure 2. Comparative Analysis of State Transition Probabilities in Human-AI Teaming Conditions

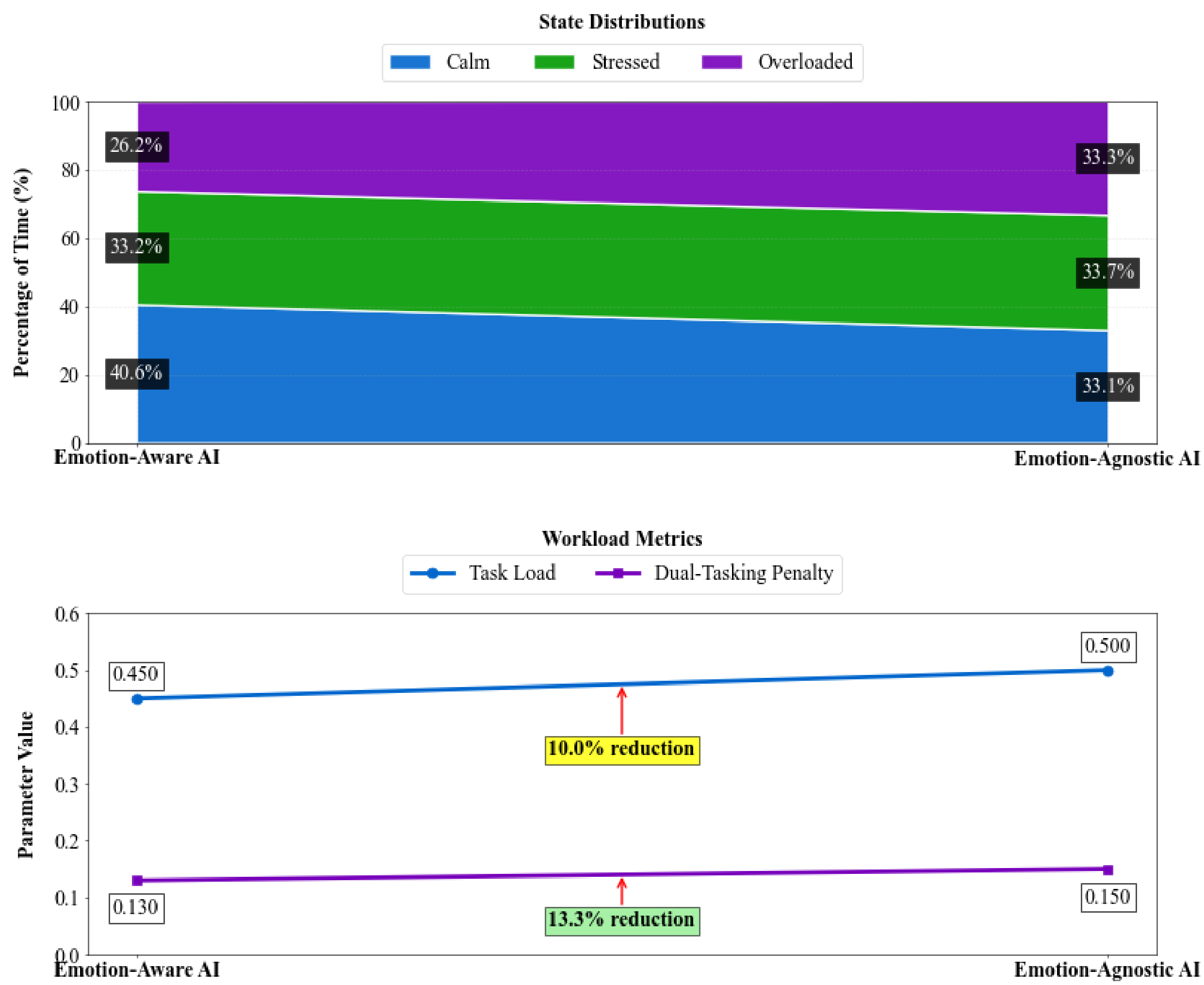

Figure 3. State Distributions and Workload Metrics Comparison

DISCUSSION

Emotion-aware AI significantly enhanced human-AI performance in high-stress situations, achieving a 22.9% improvement in calm state maintenance (40.6% vs. 33.1%) and a 21.4% reduction in overloaded states (26.2% vs. 33.3%). The large effect size (Cohen's $d = 1.04$) demonstrates substantial benefits across diverse operators, addressing gaps in human-AI teaming frameworks that often view operators as static rather than dynamic partners enhanced through intelligent adaptation (Khare et al., 2024; Vistorte et al., 2024).

Mechanisms and Performance Impact

Analysis of transition matrix shows emotion-aware AI acts as a safety net, boosting calm state stability (59.1% vs. 52.8%) and stress recovery (26.5% vs. 21.9%). It outperforms reactive strategies by proactively enhancing performance, including a 7.57 ms faster reaction time (from 345.05 ms to 337.48 ms), which is crucial in defense where milliseconds matter. Visual accuracy (0.99 vs. 0.98) and reasoning (0.95 vs. 0.94) also improved. The system adjusts task load (reductions of 0.05-0.08) and dual-task penalties (0.02-0.04), conserving resources during long operations.

Operational and Health Implications

Steady-state analysis revealed that operators spent more time in optimal cognitive states (40.6% vs. 33.1% in Calm), thereby fostering sustained resilience and cognitive well-being. This transition to resilience-focused operations has a positive impact on personnel retention, training effectiveness, and long-term psychological well-being. By managing cognitive load effectively, emotion-aware AI may help alleviate stress-related psychological injuries, including PTSD and cognitive decline, given the correlation between operational stress and psychological casualties (Price et al., 2024).

Methodological Contributions

This study establishes new standards for digital twin development by incorporating real PhysioNet physiological data, improving simulation accuracy despite challenges in adapting automotive stress data to defense applications. The discrete-event simulation framework linking Markov state transitions with preprocessed physiological data connects affective computing, human factors engineering, and defense systems design. The closed-loop feedback mechanism, where AI modifications influence physiological responses to inform future adjustments, establishes groundwork for adaptive human-AI systems that shift from static optimization to dynamic co-adaptation.

Design Guidelines and Implementation

Future emotion-aware systems should incorporate real-time physiological monitoring to identify stress states before performance decline, adaptive task allocation to prevent stress escalation while preserving human agency, and multimodal integration of physiological signals for reliable state estimation. The enhanced state stability and recovery patterns suggest that graduated stress responses manage cognitive load more effectively than binary interventions.
From a human factors perspective, successful implementation requires maintaining operator trust through transparent feedback about detected stress states and AI adaptations, while ensuring operators retain override capabilities to preserve situational control and prevent automation dependency. Training protocols should familiarize personnel with the system's stress detection capabilities and adaptation strategies to optimize human-AI collaboration. Technological integration appears feasible with current physiological monitoring technologies. Merging existing wearable sensors with mission systems could provide operational benefits without requiring significant technological advances, with a modular design allowing gradual adoption as technologies evolve.

Limitations and Future Directions

The study utilizes automotive stress data as a proxy for defense operations, revealing valuable physiological patterns that require validation in real military contexts for generalizability. The simulated EEG data, due to dataset limitations, pose a constraint that future research must address by integrating comprehensive neurophysiological monitoring, such as real EEG or fNIRS, to improve cognitive state detection accuracy.

The SVM classifier's accuracy wasn't directly validated since simulated EEG data was used. While prior research indicates an 83.3% accuracy for similar setups (Nechyporenko et al., 2024), future studies should investigate advanced machine-learning methods and additional physiological modalities to enhance the reliability of stress prediction. Validation studies should examine the effectiveness of emotion-aware AI across different scales, from individuals to teams and organizations, to clarify how individual cognitive optimization affects collective performance. Longitudinal research could explore the long-term impact of emotion-aware AI on operator development and well-being, ensuring that technology enhances rather than diminishes human capabilities.

CONCLUSION

This research establishes emotion-aware AI as a significant advancement for human-AI collaborative systems in high-stress environments. The digital twin simulation, supported by the integration of preprocessed physiological data, demonstrates that AI systems capable of monitoring and responding to human emotional states can significantly improve performance and resilience outcomes.

The 22.9% improvement in calm state maintenance, 21.4% reduction in high-risk Overloaded states, and enhanced cognitive performance metrics (e.g., 7.57 ms reaction time improvement, visual accuracy of 0.99 vs. 0.98, reasoning score of 0.95 vs. 0.94) provide compelling evidence that emotion-aware AI represents a substantial step toward human-centered AI systems that optimize collaborative potential. For defense applications, these findings suggest that emotion-aware AI could enhance mission effectiveness while protecting personnel well-being, addressing the dual imperatives of operational success and force protection. The steady-state analysis, showing sustained optimal cognitive states (40.6% vs. 33.1% Calm), indicates enduring rather than temporary benefits. The methodological innovations demonstrated here, particularly the integration of preprocessed physiological data into digital twin frameworks and the development of closed-loop adaptation mechanisms, set new standards for human-AI system design and evaluation. These approaches provide a foundation for developing increasingly sophisticated emotion-aware technologies that adapt to the complex, dynamic requirements of real-world operational environments. As human-AI teaming becomes increasingly central to organizational effectiveness across domains, the principles and technologies demonstrated in this research offer a pathway toward truly symbiotic human-AI collaboration, intelligently supporting and amplifying human potential through emotionally intelligent artificial partners.

REFERENCES

Chen, D., Yoon, H. J., Wan, Z., Alluru, N., Lee, S. W., He, R., Moore, T. J., Nelson, F. F., Yoon, S., Lim, H., Kim, D. D., & Cho, J. H. (2025). Advancing human-machine teaming: Concepts, challenges, and applications. *arXiv preprint arXiv:2503.16518v2*. https://doi.org/10.48550/arXiv.2503.16518

Corrigan, S. L., Roberts, S. S. H., Warmington, S. A., Drain, J. R., Tait, J. L., Bulmer, S., & Main, L. C. (2023). Overnight heart rate variability responses to military combat engineer training. *Applied Ergonomics*, *107*, 103935. https://doi.org/10.1016/j.apergo.2022.103935

Eddy, M. D., Hurwitz, J. B., Jacobs, G. A., Green, G., & Lucas, G. (2015). The effects of load carriage on cognitive performance. *Military Psychology*, *27*(3), 179–197. https://doi.org/10.1037/mil0000072

Gohumpu, J., Xue, M., & Bao, Y. (2023). Emotion recognition with multi-modal peripheral physiological signals. *Frontiers in Computer Science*, *5*, 1264713. https://doi.org/10.3389/fcomp.2023.1264713

Goldberger, A., Amaral, L., Glass, L., Hausdorff, J., Ivanov, P. C., Mark, R., … Stanley, H. E. (2000). PhysioBank, PhysioToolkit, and PhysioNet: Components of a new research resource for complex physiologic signals. *Circulation*, *101*, e215–e220. https://doi.org/10.1161/01.CIR.101.23.e215

Haque, Y., Zawad, R. S., Rony, C. S. A., Banna, H. A., Ghosh, T., Kaiser, M. S., & Mahmud, M. (2024). State-of-the-art of stress prediction from heart rate variability using artificial intelligence. *Cognitive Computation*, *16*(2), 455–481. https://doi.org/10.1007/s12559-023-10200-0

Healey, J., & Picard, R. (2005). Detecting stress during real-world driving tasks using physiological sensors. *IEEE Transactions on Intelligent Transportation Systems*, *6*(2), 156–166. https://doi.org/10.1109/TITS.2005.848368

Jacques, C., Quiquempoix, M., Sauvet, F., Le Van Quyen, M., Gomez-Merino, D., & Chennaoui, M. (2024). Interest of neurofeedback training for cognitive performance and risk of brain disorders in the military context. *Frontiers in Psychology*, *15*, 1412289. https://doi.org/10.3389/fpsyg.2024.1412289

Kallinen, K., & Ojanen, T. (2023). Cognitive performance changes during a 20-day winter military training course and the following 10-day recovery period. *International Journal of Circumpolar Health*, *82*, 2225896. https://doi.org/10.1080/22423982.2023.2225896

Khare, S. K., Blanes-Vidal, V., Nadimi, E. S., & Acharya, U. R. (2024). Emotion recognition and artificial intelligence: A systematic review (2014–2023) and research recommendations. *Information Fusion*, *102*, 102019. https://doi.org/10.1016/j.inffus.2023.102019

Ma, W., Zheng, Y., Li, T., Li, Z., Li, Y., & Wang, L. (2024). A comprehensive review of deep learning in EEG-based emotion recognition: Classifications, trends, and practical implications. *PeerJ Computer Science*, *10*, e2065. https://doi.org/10.7717/peerj-cs.2065

Martin, K., Périard, J., Rattray, B., & Pyne, D. B. (2020). Physiological factors which influence cognitive performance in military personnel. *Human Factors*, *62*(1), 93–123. https://doi.org/10.1177/0018720819841757

McDuff, D., Gontarek, S., & Picard, R. (2014). Remote measurement of cognitive stress via heart rate variability. In *2014 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society* (pp. 2957–2960). IEEE. https://doi.org/10.1109/EMBC.2014.6944381

Nechyporenko, A., Frohme, M., Strelchuk, Y., Omelchenko, V., Gargin, V., Ishchenko, L., & Alekseeva, V. (2024). Galvanic skin response and photoplethysmography for stress recognition using machine learning and wearable sensors. *Applied Sciences*, *14*(24), 11997. https://doi.org/10.3390/app142411997

Pande, P., Dubey, A. K., Nayyar, A., & Mahajan, R. (2023). EEG-based measurement system for monitoring student engagement in Learning 4.0. *Multimedia Tools and Applications*. Advance online publication. https://doi.org/10.1007/s11042-023-16949-3

Peabody, J. E., Ryznar, R., Ziesmann, M. T., & Gillman, L. (2023). A systematic review of heart rate variability as a measure of stress in medical professionals. *Cureus*, *15*(1), e34345. https://doi.org/10.7759/cureus.34345

Pellegrin, G., Ricka, N., Fompeyrine, D. A., Rohaly, T., Enders, L., & Roy, H. (2025). Assessment of PTSD in military personnel via machine learning based on physiological habituation in a virtual immersive environment. *Scientific Reports*, *15*, 7562. https://doi.org/10.1038/s41598-025-91916-x

Pereira da Silva, S., da Silva-Sauer, L., Gonçalves da Fonsêca, É. K., Garcia, R. B., & Fernández-Calvo, B. (2023). Neural correlates of cognitive reserve based on EEG signals: A systematic review. *Psychology & Neuroscience*, *16*(4), 317–338. https://doi.org/10.1037/pne0000327

Price, M. M., Zanesco, A. P., Denkova, E., & Jha, A. P. (2024). Examining factors associated with self-reported cognitive functioning in elite military settings: Considerations of combat experiences and post-traumatic stress symptomatology. *Scientific Reports*, *14*, 19161. https://doi.org/10.1038/s41598-024-65826-3

Raza, M. S., Murtaza, M., Cheng, C.-T., Muslam, M. M. A., & Albahlal, B. M. (2024). Systematic review of cognitive impairment in drivers through mental workload using physiological measures of heart rate variability. *Frontiers in Computational Neuroscience*, *18*, 1475530. https://doi.org/10.3389/fncom.2024.1475530

Romaniuk, M., Fisher, G., Sunderland, M., & Batterham, P. J. (2023). Development and psychometric evaluation of the mental readiness for military transition scale (MT-Ready). *BMC Psychiatry*, *23*, 575. https://doi.org/10.1186/s12888-023-05032-z

Shi, Y., Ruiz, N., Taib, R., Choi, E., & Chen, F. (2007). Galvanic skin response (GSR) as an index of cognitive load. *CHI'07 Extended Abstracts on Human Factors in Computing Systems*, 2651–2656. https://doi.org/10.1145/1240866.1241057

Solhjoo, S., Haigney, M. C., McBee, E., van Merrienboer, J. J. G., Schuwirth, L., Artino, A. R., Jr., Battista, A., Ratcliffe, T. A., Lee, H. D., & Durning, S. J. (2019). Heart rate variability as a biomarker for cognitive performance and stress in medical education: A systematic review. *Scientific Reports*, *9*(1), 14668. https://doi.org/10.1038/s41598-019-50280-3

Vine, C. a. J., Myers, S. D., Coakley, S. L., Blacker, S. D., & Runswick, O. R. (2021). Transferability of Military-Specific cognitive research to military training and operations. Frontiers in Psychology, 12. https://doi.org/10.3389/fpsyg.2021.604803

Vine, S. J., Uiga, L., Lavric, A., Moore, L. J., Tsaneva-Atanasova, K., & Wilson, M. R. (2021). Individual reactions to stress predict performance during a critical aviation incident. *Anxiety, Stress, & Coping*, *34*(4), 414–431. https://doi.org/10.1080/10615806.2020.1824143

Vistorte, A. O. R., Deroncele-Acosta, A., Ayala, J. L. M., Barrasa, A., López-Granero, C., & Martí-González, M. (2024). Integrating artificial intelligence to assess emotions in learning environments: A systematic literature review. *Frontiers in Psychology*, *15*, 1387089. https://doi.org/10.3389/fpsyg.2024.1387089

Wang, X., Ren, Y., Luo, Z., He, W., Hong, J., & Huang, Y. (2023). Deep learning-based EEG emotion recognition: Current trends and future perspectives. *Frontiers in Psychology*, *14*, 1126994. https://doi.org/10.3389/fpsyg.2023.1126994