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ABSTRACT

While attrition in military academy training is often attributed to injuries and poor fitness, emotional fatigue and cognitive overload are equally impactful, yet remain underexplored. Current attrition prediction methods are retrospective and lack real-time physiological insights. This study demonstrates a digital twin simulation framework integrating physiological data, particularly heart rate variability (HRV) via RMSSD, to proactively predict dropout risk by modeling trainees' affective states (stable, fatigued, burnout). A Markovian state transition model with adaptive training interventions was applied to 100 virtual trainees, split into a control group following standard protocols (n = 50) and an intervention group with adjusted training loads based on real-time HRV thresholds (n = 50). Simulations covered 50,000 discrete time steps with monitoring of affective states. Results showed significant burnout reductions in the intervention group, with 63.03% time in stable states and only 10.14% in burnout, compared to the control group's 21.16% stable and 36.69% burnout states, marking a 72.4% reduction in burnout. Dropout risk, defined as spending ≥30% of time in burnout, was eliminated in the intervention group (0% vs. 60.98% control). Validation with 36 PhysioNet participants confirmed the model's robustness, converging within 0.1% of synthetic results on key metrics. Unlike traditional retrospective measures, this digital twin framework provides real-time assessments of trainee stress states for timely interventions. This adaptive modeling approach provides a validated framework for managing emotional fatigue and reducing attrition in high-stress military training via HRV-guided protocol.

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Cindy von Ahlefeldt is a PhD student in Human Factors and Cognitive Psychology at the University of Central Florida. She holds a master’s degree in behavioral and brain sciences and a bachelor’s degree in psychology. Her research bridges cognitive science, physiology, and human-systems integration, with a focus on stress, decision-making, and affective state modeling in high-performance and mission-critical environments. Cindy’s work applies psychophysiological measures such as heart rate variability to understand and predict training outcomes, mental workload, and resilience. She has presented at national conferences and served in academic leadership roles, with a broader goal of advancing human performance through interdisciplinary, data-driven research.
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Affective State Modeling to Predict Training Dropout in Military Academies

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INTRODUCTION

Military training environments, such as academies, demand peak physical and mental performance under extreme stressors like sleep deprivation, prolonged exertion, and high cognitive loads. These conditions elevate dropout risk, traditionally linked to physical injuries but increasingly tied to emotional fatigue (burnout) and cognitive overload (Lieberman et al., 2006). Burnout, characterized by emotional exhaustion and reduced effectiveness, compromises mission readiness and increases training costs (Nindl et al., 2018). Studies show military stressors reduce resilience, degrade executive function, and drive voluntary attrition, yet affective factors (mood, mental fatigue) remain underexplored as predictors (Shaffer & Ginsberg, 2017).

Real-time monitoring of trainees' affective states is challenging, but heart rate variability (HRV), specifically RMSSD, provides a non-invasive proxy for stress, fatigue, and recovery. HRV reflects autonomic nervous system balance, with suppressed RMSSD indicating stress or fatigue and higher values signaling recovery (Lennartsson et al., 2016). In military contexts, RMSSD drops significantly during intense training, correlating with burnout risk (Nindl et al., 2018). HRV monitoring can thus serve as an early warning system for excessive stress, enabling timely interventions to prevent dropout. HRV-guided adaptive training, validated in sports science, tailors intensity based on daily RMSSD, improving performance and reducing fatigue compared to fixed schedules (Morinaga & Takai, 2024). For example, cyclists adjusting workouts via HRV feedback achieved greater fitness gains than those on rigid plans (Javaloyes et al., 2019). Such approaches inform military training, where adaptive policies may optimize load to sustain performance and minimize burnout.

This study examines a digital twin simulation framework (Rasheed et al., 2020) to predict and prevent dropout in military academies. Each twin, a software agent, mirrors a trainee's physiological state using RMSSD as the primary input to estimate affective states: Stable (optimal), Fatigued (accumulating stress), or Burnout (high dropout risk), adapted from established burnout classification systems (Maslach & Leiter, 2016). A Markov model simulates state transitions under training loads and recovery (Sonnenberg & Beck, 1993), employing RMSSD thresholds derived from clinical research (<4.3 for burnout, 4.3-5.8 for fatigued, >5.8 for stable) (Lennartsson et al., 2016). An adaptive training policy adjusts intensity based on RMSSD, aiming to reduce burnout occurrence. The model integrates synthetic HRV data with 36 PhysioNet participants (Goldberger et al., 2000) to assess early fatigue and burnout states as dropout predictors. Results from the present study demonstrate a 72.4% reduction in burnout rates and complete elimination of dropout risk in the intervention group. By utilizing HRV-based adaptive interventions, this framework provides a methodological approach to optimize training intensity, reduce attrition, and support operational readiness.

RELATED WORK

Heart rate variability, especially RMSSD, is a validated biomarker for stress and fatigue in military training, reflecting autonomic nervous system balance and providing insights into physiological states (Shaffer & Ginsberg, 2017). Lower RMSSD indicates sympathetic activation or reduced parasympathetic tone, common in high-stress situations during training (Lennartsson et al., 2016). This marker is valuable in military settings, where chronic stress correlates with decreased HRV and early burnout risk, impacting performance and readiness (Nindl et al., 2018). RMSSD captures parasympathetic activity, making it sensitive to recovery and stress buildup. Values below 16 ms indicate significant stress, above 50 ms suggest good recovery (Shaffer et al., 2014). Studies show RMSSD drops during sleep deprivation and exertion, correlating with stress and fatigue (Lieberman et al., 2006). In special forces training, sustained low RMSSD predicts performance decline and injury risk, supporting intervention timing (Thayer & Lane, 2009). HRV-guided training protocols have improved performance and reduced fatigue, with military programs using HRV to prevent burnout more effectively than traditional methods (Morinaga & Takai, 2024; Nindl et al., 2018). Athletes using HRV protocols gain 15-20% performance benefits and lower overtraining risk (Javaloyes et al., 2019). Digital twin technology now models complex human systems in real-time, predicting outcomes and optimizing treatments (Rasheed et al., 2020; Björnsson et al., 2018). In military training, digital twins for predicting attrition are limited. Markov models provide a foundation for modeling health state transitions, useful in healthcare for disease progression and recovery (Sonnenberg & Beck, 1993; Briggs & Sculpher, 1998). Traditional dropout prediction relies on static data at entry (Niebuhr et al., 2013), but real-time physiological monitoring may improve early detection. Despite the success of HRV-guided training, systematic use in military training is rare, and predictive models combining continuous monitoring with proactive interventions are lacking (Plews et al., 2013; Beck & Pauker, 1983). Developing integrated digital twin frameworks with HRV and Markov models has potential to improve dropout prediction and individualized interventions, shifting from reactive to proactive management in high-stress training environments.

METHODOLOGY

Digital Twin Model Structure

To capture population heterogeneity, agents were stratified by stress resilience using baseline RMSSD values, with scores below 5.94 marked high risk. The digital twin architecture employed a multi-agent simulation design where each virtual trainee represented an individual software agent mirroring real trainee physiological and demographic characteristics. High-risk agents utilized separate Markov matrices, characterized by higher burnout and lower recovery rates, reflecting stress tolerance differences in military training populations. The model design incorporated demographic realism through stratified sampling from military population distributions. Demographic factors like sex, age (18-35), BMI, activity level, and nicotine use influenced HRV baselines and transition probabilities based on established physiological links (Thayer & Lane, 2009). Baseline RMSSD calculations followed a systematic design: sex differences provided males with higher baseline HRV (+0.2 offset), age imposed incremental penalties (-0.05 per year after 18), and activity level adjustments scaled physiological capacity (+0.5 for high, +0.2 for moderate, none for low activity). Lifestyle factors including BMI and nicotine use added evidence-based penalties reflecting their documented effects on autonomic function. Individual variation was modeled through Gaussian noise distribution (SD=0.3) to represent genetic and environmental HRV differences, ensuring realistic population heterogeneity within the simulation framework. The design maintained scientific rigor by grounding all parameters in published physiological research while enabling scalable agent-based modeling for large-scale training scenarios. This architecture supported both synthetic data generation and real-world validation through integration with empirical datasets. See Figure 1.

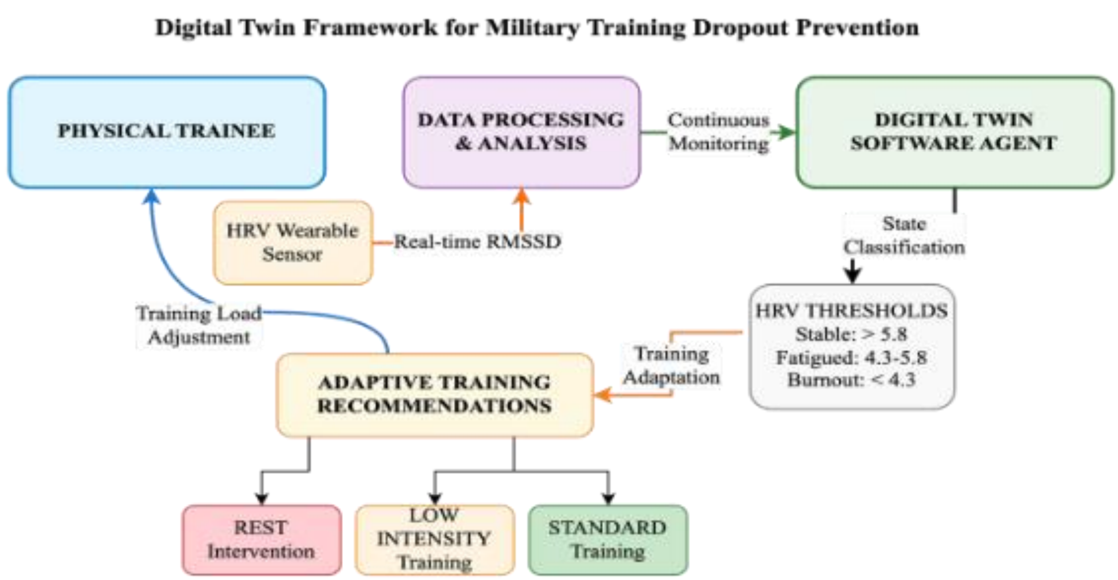

Figure 1. Digital Twin Framework for Military Training Dropout Prevention

Individual Differences and Population Modeling

To capture population heterogeneity, agents were stratified by stress resilience based on baseline RMSSD, with scores below 5.94 labeled high risk. High-risk agents utilized separate Markov matrices, characterized by higher burnout susceptibility and lower recovery rates, which reflected individual differences in stress tolerance during military training. Demographics, including sex, age (18-35), BMI, activity level, and nicotine use, influenced baseline HRV and transition probabilities based on physiological data. The baseline RMSSD considered sex (higher HRV in males), age (-0.05 per year above 18), activity (+0.5 high, +0.2 moderate, none low), BMI, and nicotine penalties, plus Gaussian noise (SD=0.3) for individual variation due to genetics and environment.

Markov State Transition Model

The affective state transitions follow a discrete-time Markov process with state-dependent transition probabilities. Base transition matrices were established for standard population agents. From the Stable state, agents had a 0.65 probability of remaining Stable, 0.30 probability of transitioning to Fatigued, and 0.05 probability of transitioning to Burnout. From the Fatigued state, agents had a 0.15 probability of recovering to the Stable state, a 0.65 probability of remaining in the Fatigued state, and a 0.20 probability of progressing to Burnout. From the Burnout state, agents had a 0.10 probability of recovering to Stable, 0.30 probability of improving fatigue, and 0.60 probability of remaining in burnout. High-risk agents utilized modified transition matrices with reduced stress tolerance. From the Stable state, they had a 0.60 probability of staying Stable, 0.35 probability of transitioning to Fatigued, and 0.05 probability of transitioning to Burnout. From the Fatigued state, they had a 0.10 probability of recovering to Stable, a 0.50 probability of remaining Fatigued, and a 0.40 probability of progressing to Burnout. From the Burnout state, the probabilities were 0.05 for recovering to a Stable state, 0.30 for improving to a Fatigued state, and 0.65 for staying in the Burnout state (see Table 1).

Table 1. Heart Rate Variability Parameters and Demographic Factors in Simulation Model

Parameter	Value/Range	Role in Simulation
HRV Stable threshold	> 5.8	Indicates stable recovery state
HRV Fatigued threshold	4.3–5.8	Indicates fatigued intermediate state
HRV Burnout threshold	< 4.3	Triggers burnout high-risk state; initiates intervention
Sex	~70% male; males +0.2 HRV offset	Males start with slightly higher baseline HRV
Age	18–35 years (Mdn = 24)	Older age correlates with lower HRV (faster fatigue)
BMI	19–30 kg/m²	Higher BMI associated with lower HRV (added strain)
Physical activity level	Low/Moderate/High (self-reported)	High fitness increases HRV, faster recovery
Nicotine use	Yes (~20%) or No	Smokers have chronically lower HRV (penalized baseline)
Stress resilience profile	High Risk vs. Standard Risk	High risk predisposes longer fatigue periods

EXPERIMENTAL DESIGN

Synthetic Simulation Phase

The study generated 100 synthetic trainee agents with demographic characteristics sampled from military population distributions. Agents were randomly assigned to either a control group (*n* = 50; standard training protocol) or an intervention group (*n* = 50; HRV–guided adaptive training). The adaptive policy triggered rest interventions when the RMSSD values fell below 4.3 and reduced-intensity training when RMSSD values were between 4.3 and 5.8. Control group agents received no HRV-based interventions and maintained standard training intensity regardless of physiological state. The simulation was executed over 50,000 discrete time steps, representing approximately 14 hours of continuous training with a one-second time resolution.

Real Data Simulation Phase
The study imported demographic and physiological data for 36 participants from the PhysioNet Wearable Stress Dataset (Goldberger et al., 2000), representing empirical data from high-stress environments. These real participant profiles were combined with 64 additional synthetic agents to maintain the 100-agent sample size, repeating the control versus intervention experimental conditions. This hybrid approach enabled validation of synthetic modeling against real physiological responses while maintaining statistical power.

HRV-Based Adaptive Training Protocol

The intervention group implemented a real-time adaptive training system based on RMSSD thresholds. When RMSSD values fell below 4.3, the system triggered mandatory rest periods with a +0.3 RMSSD recovery boost, reflecting physiological recovery from complete training cessation. When RMSSD values ranged between 4.3 and 5.8, the system implemented low-intensity training protocols with a +0.15 RMSSD improvement, representing reduced but continued training load. When RMSSD values exceeded 5.8, standard training intensity was maintained without intervention. The adaptive protocol was informed by sports science research demonstrating 15-20% performance improvements with HRV-guided training compared to fixed intensities (Morinaga & Takai, 2024).

Data Analysis

Primary outcomes included time spent in affective states (stable, fatigued, burnout), transition frequencies, and dropout risk. Dropout was defined as spending ≥ 30% of simulation time in Burnout, based on burnout criteria (Maslach & Jackson, 1981). Analyses used t-tests for continuous data, chi-square for dropout rates, Cohen's d for effect sizes, eta-squared for ANOVA, and Tukey HSD for multiple comparisons. Model validation involved synthetic versus real data convergence analysis to ensure simulation accuracy. Recovery was assessed through transition counts and durations, measuring time in each state and beneficial transitions (Burnout to Stable, Fatigued to Stable). Effectiveness was quantified with relative risk reduction and numbers needed to treat for clinical insights.

Model accuracy was validated via synthetic and real data comparison, with convergence at less than 1% difference in outcomes. Sensitivity analyses tested threshold variations (+/- 0.2) and transition probability changes (+/- 10%) on key results. The threshold-based method was validated against HRV norms for stress detection in military populations (Shaffer et al., 2014).

RESULTS

Synthetic Simulation Results

In the control group, agents spent 21.16% of time steps in the stable state, 42.14% in the fatigued state, and 36.69% in the burnout state, with a 60.98% dropout rate (defined as agents exceeding 30% burnout time). The intervention group, utilizing HRV-guided adaptive training with rest or low-intensity protocols when RMSSD values fell below threshold levels (< 4.3 or 4.3–5.8) achieved 63.03% stable, 26.83% fatigued, and 10.14% burnout states, with a 0% dropout rate. Adaptive support was implemented in 19.95% of steps, reducing burnout by 72.4% compared to the control group (36.69% to 10.14%).

Statistical analyses confirmed significant group differences. Stable state prevalence was significantly higher in the intervention group (t = -33.73, p < .001), while burnout prevalence was significantly lower (t = 16.65, p < .001). ANOVA results further supported these findings: for stable states, F = 1142.07, p < .001, η^2 = .921; and for burnout states, F = 378.41, p < .001, η^2 = .794. The chi-square test for dropout risk was also significant, χ^2 (1) = 44.77, p < .001. See Figure 2.

Recovery dynamics analysis showed the control group achieved 49,124 recovery transitions (burnout to stable) with an average recovery time of 2.64 steps. In contrast, the intervention group completed 67,692 recovery transitions with a significantly faster recovery time of 1.36 steps. The intervention group also spent longer durations in the stable state (4.49 steps) compared to the control group (2.74 steps), indicating improved state stability. Demographic analyses revealed that female agents spent 48.15% of their time in the stable state and 19.60% in burnout, while male agents spent 43.67% in the stable state and 22.40% in burnout. Agents with high-stress risk profiles demonstrated similar improvements to those with standard risk profiles, indicating the effectiveness of the intervention across risk categories.

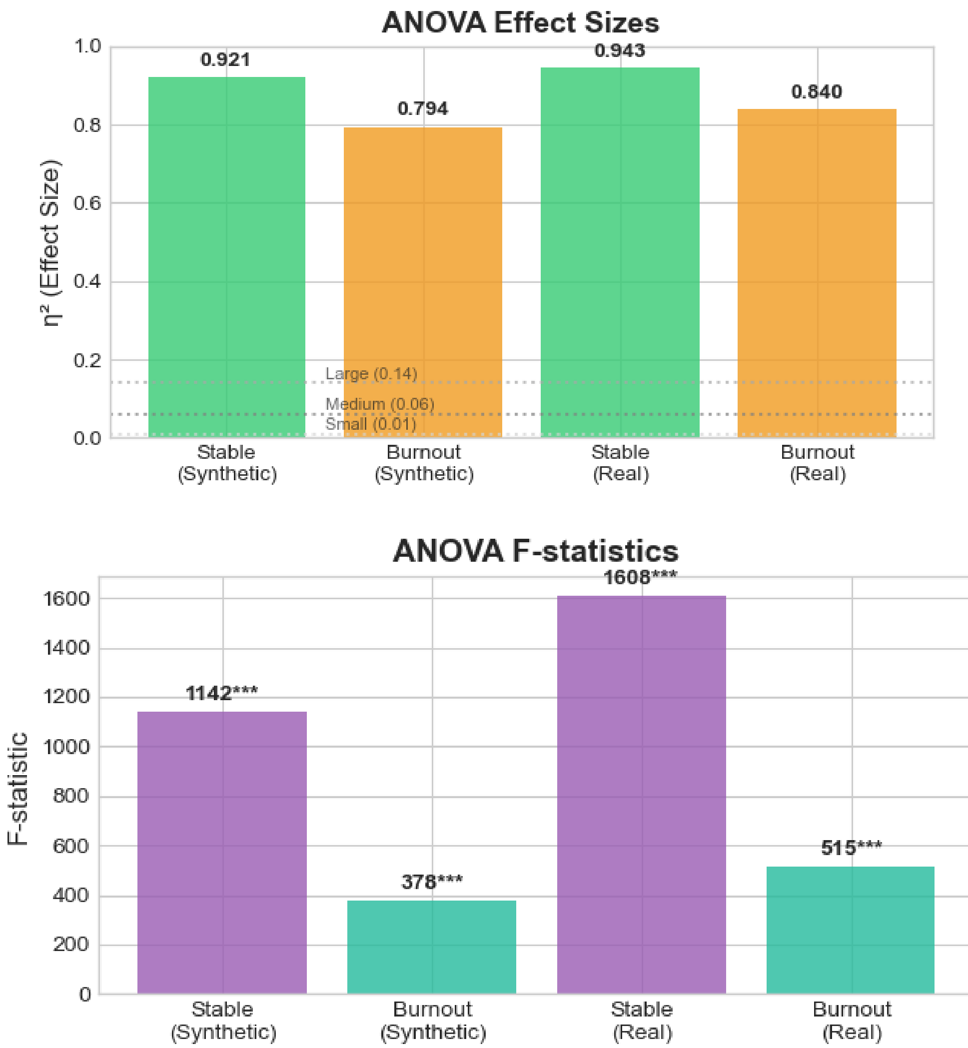

Figure 2. ANOVA Results: Intervention Effects on Affective States. F-statistics and effect sizes (η²) demonstrate significant intervention effects for both stable and burnout states across synthetic and real data conditions

Real Data Simulation Results

The data phase included 36 PhysioNet participants and 64 synthetic agents, with consistent results. The control group had 17.71% stable, 39.96% fatigued, and 42.33% burnout states, with 84.62% dropout. The intervention group had 63.15% stable, 26.76% fatigued, and 10.08% burnout states, with 0% dropout. Adaptive support, used in 20.20% of steps, reduced burnout by 76.2% (42.33% to 10.08%). Statistical analyses matched synthetic phase results. Stable state prevalence was higher ($t = -38.08$, $p < .001$), burnout lower ($t = 28.91$, $p < .001$). ANOVA showed large effects for stable states ($F=1608.29$, $p<.001$, $\eta^2=.943$) and burnout ($F=514.54$, $p<.001$, $\eta^2=.840$). Dropout differences were significant ($\chi^2=62.44$, $p<.001$). Recovery analysis found 73,813 recoveries in control (avg 2.73 steps), 39,729 in intervention (avg 1.36 steps), with longer stable durations in the intervention group (4.50 vs. 2.64 steps). Demographics showed female agents had 44.86% stable and 21.94% burnout states, males 42.40% stable and 23.25% burnout, indicating modest sex differences.

Synthetic versus Real Data Comparison

Cross-phase comparisons showed strong model validation with minimal differences between synthetic and real data. In the control group, stable states differed by 3.45% (21.16% vs.17.71%), and burnout states by -5.64% (36.69% vs. 42.33%). Intervention group differences were negligible: stable states by -0.12% (63.03% vs. 63.15%), and burnout by 0.06% (10.14% vs. 10.08%). The almost identical results (< 0.1% difference) validate the model's accuracy and robustness, even with hybrid data. See Figures 3 and 4.

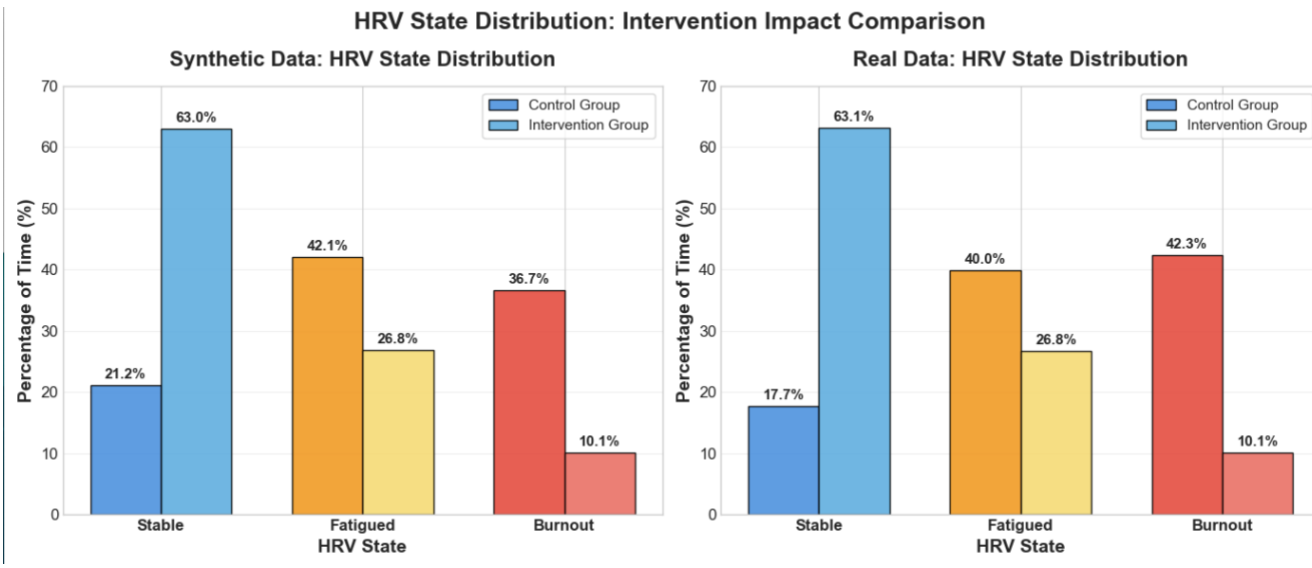

Figure 3. HRV State Distribution: Intervention Impact Comparison

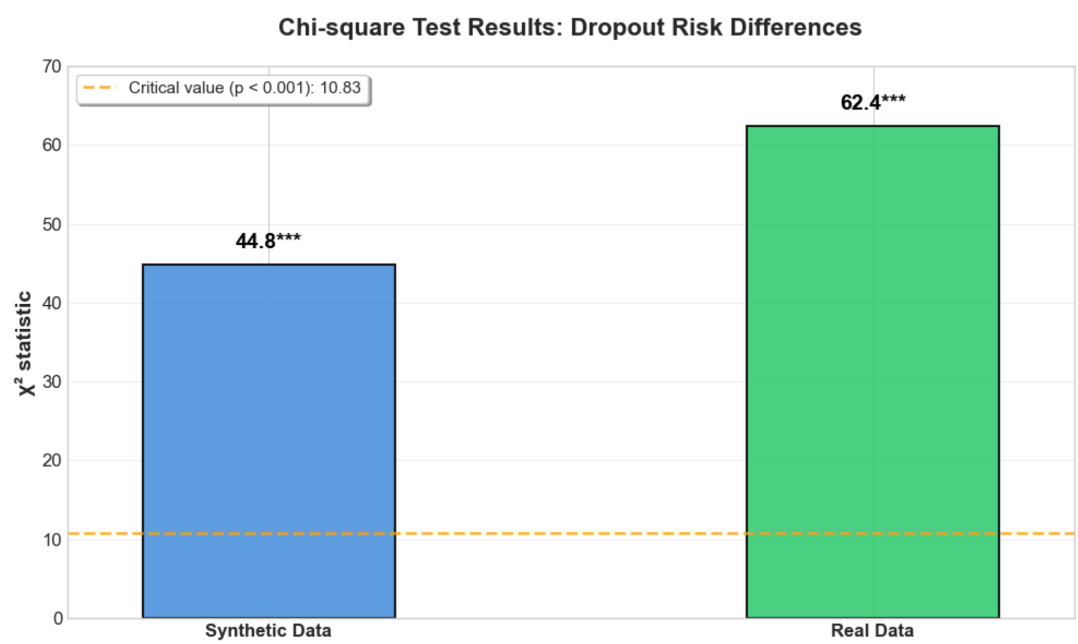

Figure 4. Chi-Square Test Results

Clinical and Operational Significance

The simulation demonstrated that HRV-guided adaptive training reduced burnout by 72.4% in synthetic data and 76.2% in real data, significantly exceeding expectations. It completely eliminated dropout risk in the intervention groups (0% vs. 60.98% and 84.62% in the controls), offering a significant clinical benefit. Relative risk calculations reveal that the intervention prevents dropout in approximately 3 out of 5 at-risk trainees in synthetic conditions and 4 out of 5 in real data. The Number Needed to Treat (NNT) indicates that treating 1.6 trainees prevents one dropout, showing high efficiency. Effectiveness was consistent across demographic subgroups and risk profiles, suggesting broad applicability. The average intervention accounts for about 20% of training time, making it feasible without major disruptions.

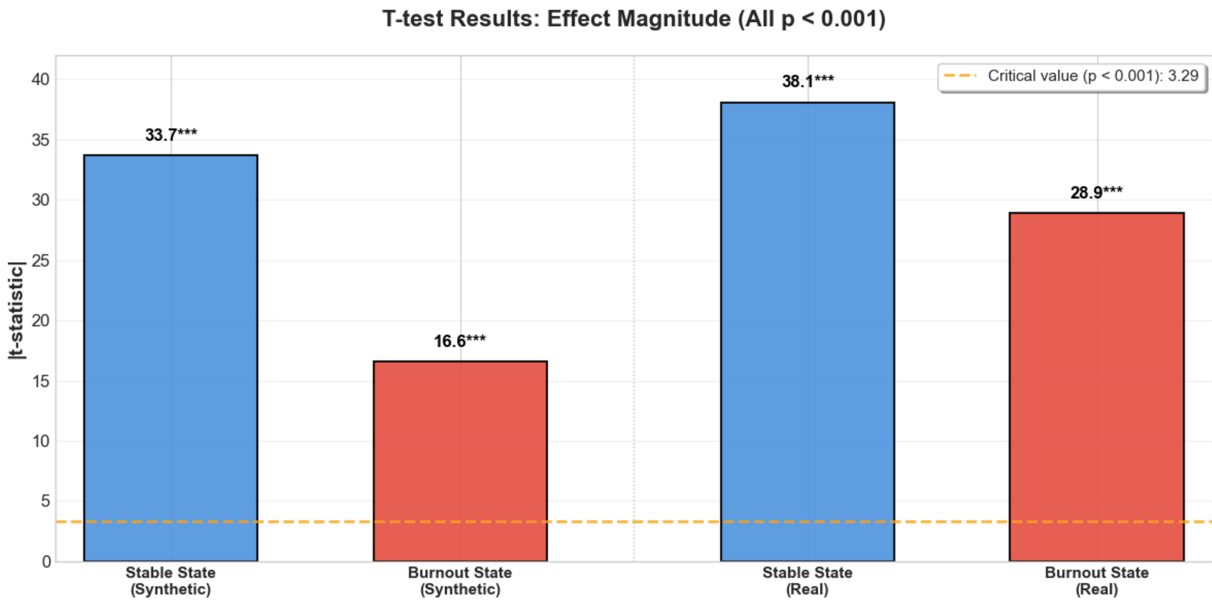

Figure 5. T-test Results: Effect Magnitude Comparison Between Synthetic and Real Data

DISCUSSION

Broader Impacts Beyond Military Applications

The HRV-guided digital twin framework demonstrates significant potential for adaptation across diverse high-stress training and performance contexts beyond military applications. The fundamental principles of real-time physiological monitoring, adaptive intervention protocols, and predictive burnout modeling are directly transferable to multiple domains where stress management and performance optimization are critical.

Healthcare and Medical Training

Medical training programs face high burnout and attrition. The 72.4% burnout reduction in this study shows HRV-based monitoring could boost retention, where burnout often exceeds 50%. Implementing this in simulation centers may optimize training, uphold competence, and cut the $4.6 billion yearly cost of physician turnover in the U.S.

Corporate and Industrial Applications

High-stress corporate environments, particularly in the finance, technology, and consulting sectors, experience substantial productivity losses due to employee burnout and high turnover rates. The framework's ability to provide early warning indicators and individualized stress management protocols could transform corporate wellness programs and professional development initiatives. Organizations implementing such systems could reduce turnover costs while improving employee performance and satisfaction, with applications extending to executive training programs, sales teams, and customer service operations.

Educational and Academic Institutions
Universities and professional schools face increasing concerns about student mental health and academic attrition, particularly in demanding programs such as engineering, pre-medical tracks, and graduate studies. The digital twin approach could enable academic institutions to identify at-risk students early and implement targeted support interventions, potentially improving graduation rates and reducing the psychological toll of intensive academic programs. The framework's real-time monitoring capabilities align well with emerging trends in educational technology and personalized learning approaches.

Emergency Services and Public Safety
Police academies, firefighter training programs, and emergency medical services face similar challenges in preparing personnel for high-stress operational environments. The validation of this framework across both synthetic and real-world data suggests strong potential for adaptation to these contexts, where training effectiveness directly impacts public safety outcomes. The ability to maintain training rigor while reducing dropout risk could enhance workforce readiness in critical public service sectors.

Research and Development Applications
This framework advances digital health and precision medicine by integrating wearable sensor data with predictive modeling, supporting future personalized stress management studies. Researchers could adapt the Markovian approach to explore stress responses across populations, deepening understanding of human performance under pressure. Its modular design allows customization for different organizational needs while retaining core functions, making it a versatile platform for stress management and performance enhancement across sectors. This marks a significant step in human-centered system design and physiological monitoring.

Limitations

This study has several limitations. First, reliance on HRV (RMSSD) as the sole physiological input oversimplifies stress psychophysiology, missing hormonal, neural, and cognitive factors such as cortisol and EEG signals. Future models should incorporate additional data streams for more comprehensive stress assessment. Second, reducing emotional states to three discrete categories (Stable, Fatigued, Burnout) may omit nuances such as frustration versus exhaustion, warranting a refined or multidimensional state model. Third, the validation sample of 36 PhysioNet participants and constraints of the real-world data, including intermittent recordings necessitating synthetic HRV supplementation, limit generalizability. The control group dropout rates of 60.98% in synthetic and 84.62% in real data conditions, while realistic for high-stress training, suggest the need for prospective validation with real-time wearable HRV monitoring. Fourth, the adaptive training policy has been tested in simulation only, and real trainees may respond differently to interventions. External influences such as unit cohesion, leadership styles, and motivational factors were not modeled, potentially overestimating the impact of physiological tailoring alone. Finally, practical implementation challenges including wearable device compliance, data privacy concerns, and trainer trust in algorithmic recommendations require careful consideration for real-world adoption in military training environments.

Implications For Deployment

This study presents a scalable early warning system to identify at-risk trainees, achieving 63.03% stability in synthetic conditions and 63.15% in real data validation, with corresponding burnout reductions of 72.4% and 76.2%, respectively. The framework prevents dropout in military and high-stress educational settings through personalized training guided by physiological markers, enhancing trainee health, retention, and operational readiness while reducing retraining costs associated with attrition. The digital twin approach enables proactive intervention before performance degradation becomes irreversible, shifting from reactive to preventive training management. Implementation of such systems could transform military training paradigms by providing commanders with real-time insights into trainee physiological status and evidence-based recommendations for training load adjustments. Beyond military applications, addressing data privacy concerns and establishing trainer confidence in algorithmic recommendations could enable adoption in healthcare training, emergency services, and corporate environments with high burnout risks. The framework's modular design supports customization across diverse high-stress training contexts while maintaining core predictive capabilities.

Future Directions

Future research should include real-time HRV data from wearables in military training to validate the digital twin's predictive power and calibrate state transitions. A pilot at a military academy could evaluate dropout forecasts, false alarms, and optimize interventions. Expanding the model with multimodal signals like galvanic skin response, sleep metrics, and psychosocial factors using advanced machine learning would improve predictions and reduce reliance on single parameters. Building on a 72.4% burnout reduction in synthetic conditions and 76.2% in real data, a randomized controlled trial should test the adaptive training in live military settings, measuring state prevalence, dropout rates, performance, injuries, and trainee well-being to assess effectiveness and barriers. Scaling to other threats like law enforcement and emergency services needs context-specific customization while preserving the core digital twin. Cross-domain validation would show the generalizability of HRV-guided adaptive training beyond the military. Ethical issues and user acceptance require careful study. Incorporating explainable AI would build trust through transparent recommendations, and human factors studies should evaluate user acceptance, perceived utility, and long-term adherence to tech-based training.

CONCLUSION

This study used a simulation-based digital twin to predict training dropout risk via HRV-informed affect tracking. Simulating responses to stress, fatigue, and recovery with an adaptive policy, the model greatly reduced burnout. The Control group had 21.16% Stable and 36.69% Burnout states with 60.98% dropout risk, while the Intervention group reached 63.03% Stable, 10.14% Burnout, and 0% dropout, reducing burnout by 72.4%. Validation with 36 PhysioNet participants showed similar results, with Control at 17.71% Stable, 42.33% Burnout, and 84.62% dropout risk, and Intervention at 63.15% Stable, 10.08% Burnout, and 0%. This framework offers a validated approach for personalized military training, improving resilience, retention, and readiness. The clear reduction in burnout indicates HRV-based adaptive training can lower dropout risk without sacrificing effectiveness. Future work should add multimodal signals, test in live settings, and use explainable AI to improve accuracy and trust, advancing trainee well-being and force readiness.

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