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Machine Learning-Driven Prediction and Personalized Intervention for Athlete Burnout: Integrating Biometric and Psychological Markers

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ABSTRACT

Objective: Athlete burnout, which is a multidimensional syndrome and consists of emotional exhaustion, reduced accomplishment, and sport devaluation, is associated with detrimental outcomes to performance and well-being. The aim of this study was to design and validate a machine learning model by combining real-time physiological monitoring and psychological testing to predict and prevent burnout in elite athletes. **Method:** We recorded multimodal data for 120 national-level athletes (60 males, 60 females) from three sports over a 6-month period; we obtained heart rate variability (HRV), salivary cortisol, sleep measures, and standardized burnout scales. An ensemble model of XGBoost and LSTM architectures had the best predictive performance (AUC-ROC = 0.91), which was significantly better than that of the traditional logistic regression (AUC-ROC = 0.72, $p < 0.001$). **Results**: Distinguishing physiological predictors were HRV ($\beta = -0.34$, $p < 0.001$), cortisol awakening response attenuation ($\beta = 0.29$, $p = 0.001$), and deep sleep reduction ($\beta = -0.27$, $p = 0.001$), with the relationships being moderated by TrL (pinteraction < 0.05). In the three-month implementation trial, the system prospectively identified 68% of the burnout cases early on (median lead time = 18 days); it decreased the incidence by 37% relative to the controls (OR = 0.43, 95% CI [0.28, 0.66]). The model had strong temporal stability (AUC drift < 0.02/month), but there is potential for decreased generalizability to recreational athletes and technology-based restricting widespread application. **Conclusions**: Our results demonstrate the potential for machine learning-empowered combinatory continuous biometric monitoring and psychological screening to operationalize burnout as a preventive (rather than reactive) challenge in elite sports. The model offers coaches and medical teams' actionable information to intervene in an individualized manner, but future research is needed to examine menstrual cycle effects and to design cost-effective interventions in youth sports systems.

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Introduction

Athlete burnout, a syndrome defined by emotional exhaustion, diminished sense of accomplishment and sport devaluation, has recently been recognized as a phenomenon of importance in elite level sports with negative consequences on performance, mental health and career longevity (1). The traditional method of burnout has tended to focus quite heavily on self-report questionnaires (such as the ABQ) - which are important but are also flawed due to retrospective bias and lack of real time physiological dynamics (2). Recent developments at the intersection of AI and wearable technologies have unlocked unprecedented opportunities for enabling early and objective detection of burnout risk via multimodal data fusion. Nevertheless, the use of machine learning (ML) to predict and attenuate burnout continues to be in its infancy in transforming psychometric tests into biometric measures such as heart rate variability (HRV), cortisol levels, and sleep pattern measurements (3). This gap is addressed by this study which proposes an AI-based model which combines both psychological and physiological markers which can be used to implement proactive, personalized intervention for the elite athletes.

The increase in requirements in the context of competitive sports, in the combination of high training loads and psychological pressure raises the burnout among elite athletes to an alarming degree. Studies have found that as many as 35% of professional athletes report experiencing clinically significant burnout symptoms during their careers (4). The implications go beyond performance degradation to higher injury rates, depression and early career retirement (5). Although burnout is common, it is frequently recognized too late, in part because of the subjective nature of extant diagnostic criteria and the stigma associated with mental health disclosure in sport (6). There are now indications that physiological biomarkers such as abnormal HRV patterns, increased nocturnal cortisol, and a derangement of sleep architecture could act as early warning signals of burnout before self-reported symptoms by weeks or even months.

However, to date, no investigation has combined these biomarkers with psychological data in order to develop a predictive ML model to flag athletes at risk before their visitable symptoms occur.

Artificial intelligence and machine learning methods have changed our approach to personalized medicine by identifying subtle patterns in heterogeneous data sets, but their use in sport psychology is underdeveloped. In the field of heart health, ML models drawing on HRV and activity data have in fact been able to accurately identify stress and overtraining syndromes in 85 %+ of cases (7). Likewise, NLP of athletes' spoken or written reflections has demonstrated potential to identify early indicators of mental fatigue (8). Nevertheless, the current research on burnout based on ML focuses exclusively on psychological questionnaires or isolated parameters of biometric measurements and fail to take advantage of the interplay between different types of data (9). For example, in a recent study by Kellmann et al. (10) also showed that adding ABQ scores to actigraphy data could enhance the prediction of burnout by 22% when comparing to self-report questionnaires. Expanding on these findings, our study presents a new ML ensemble approach that integrates real-time wearable data (e.g., WHOOP, Garmin), hormonal levels (salivary cortisol) and conventional validated psychometric scales to improve dynamic risk scores of burnouts.

The present research is based, theoretically, on the Allostatic Load Model, a model that hypothesizes that long-term exposure to stress results in disrupting physiological systems, resulting in burnout (11). Utilizing ML, we have operationalized this model to predict when athletes' responses begin to show early deviations away from their psychological or somatic health baselines such as attenuated HRV recovery and/or an attenuated CAR which precede symptoms of psychological Burnout (12). Most importantly, our approach accommodates explainable AI (XAI) methods, which allows coaches and sport psychologists to interpret model outputs and customize interventions. For instance, SHAP (Shapley Additive Explanations) values may show that sleep efficiency is the most important feature for burnout risk in an athlete, suggesting targeted sleep hygiene guidelines (13).

The shift from reactive to preventive mental health care in sports marks a turning point in how we support athletes. But as we integrate AI into athlete monitoring, ethical concerns can't be ignored—data privacy, algorithmic bias, and the risk of relying too heavily on technology remain critical issues (14). To address these, our approach follows GDPR standards, puts athletes in control of their data sharing, and combines AI with human oversight to ensure fairness and clinical usefulness (15). Early tests with 50 elite swimmers showed promising results: our system detected 78% of burnout cases 3–4 weeks earlier than traditional methods, with fewer than 12% false positives (unpublished data). This highlights AI's potential to transform how we protect athletes' well-being.

Our work advances the field in three key ways: (1) It's the first ML model to combine real-time biometric and psychological data for burnout prediction; (2) It computationally validates the Allostatic Load Model by mapping stress responses; and (3) It provides a practical, personalized tool for burnout prevention. By merging insights from sport psychology, physiology, and computer science, we're redefining how burnout is spotted and managed in high-pressure environments. Next steps? Adapting the model for sport-specific demands and cultural differences in burnout (16). As elite sports keep pushing boundaries, our AI-driven solution offers a science-backed way to protect both performance and mental health—ensuring the champions of tomorrow thrive.

Materials and methods

Research design

This study employed a longitudinal, mixed-methods design combining daily biometric monitoring with periodic psychological assessments to develop and validate a machine learning (ML) model for athlete burnout prediction.

Participants

A cohort of 120 elite athletes (60 male, 60 females; mean age = 23.4 ± 3.1 years) was recruited from national-level swimming, track and field, and basketball programs. Participants met inclusion criteria if they had competed at the national level for ≥2 years, trained ≥15 hours weekly, and were free from acute injury or diagnosed psychiatric conditions at baseline. The sample size was determined via power analysis (G*Power 3.1) based on prior ML studies in sport psychology ($\beta = 0.80$, $\alpha = 0.05$, effect size $f^2 = 0.25$), accounting for an anticipated 15% attrition rate over the 6-month monitoring period.

Tools and Measures

Biometric Data Collection

Physiological data were captured through a multimodal wearable system, including autonomic function, endocrine markers, and sleep/wake patterns. Continuous heart rate variability (HRV) was measured using Polar H10 chest straps sampling at 1000 Hz, with time-domain metrics (RMSSD, SDNN) and frequency-domain metrics (LF/HF ratio) extracted via Kubios HRV Premium software (17). Athletes wore sensors during sleep and training sessions, with data excluded if artifacts exceeded 5% of the recording time. For endocrine markers, salivary cortisol was collected at awakening (CAR), 30 minutes post-awakening, and 10 PM using Salivettes (Sarstedt AG), then analyzed in duplicate via ELISA (Salimetrics LLC), demonstrating an intra-assay CV below 7%. The diurnal slope was calculated as the linear decline from peak to nadir (18). Sleep architecture—including REM, deep sleep, latency, and efficiency—was quantified using WHOOP 4.0 bands, leveraging validated actigraphy algorithms (19).

Psychological Assessments

Burnout symptoms were evaluated monthly using the Athlete Burnout Questionnaire (ABQ-15), a 15-item scale measuring emotional exhaustion ($\alpha = 0.88$), reduced accomplishment ($\alpha = 0.82$), and devaluation ($\alpha = 0.79$) (20), with responses recorded on 5-point Likert scales. Additionally, ecological momentary assessments (EMA) delivered via a mobile app captured daily stress logs, prompting athletes to rate training stress (1–10 scale) and mood (PANAS-SF) three times daily (21).

Machine Learning Pipeline

Feature Engineering

A total of 147 features were extracted from raw data, including temporal features such as 7-day rolling averages of HRV, cortisol AUCg, and sleep efficiency, alongside cross-modality interaction terms (e.g., HRV reactivity to cortisol spikes) and psychological covariates like ABQ subscale trends and EMA stress variability. Missing data (less than 8%) were imputed using multivariate chained equations (MICE), and features were standardized using z-scores.

Model Development

Three machine learning architectures were compared: an XGBoost model optimized via Bayesian hyperparameter tuning (100 iterations), an LSTM network with two 64-unit layers and dropout (0.3) for time-series processing, and an ensemble model that stacked predictions from XGBoost and LSTM using a logistic meta-learner. The dataset was split temporally, with the first four months (80%) for training and the remaining two months (20%) for testing. Five-fold time-series cross-validation was employed to prevent data leakage.

Explainability

SHAP (SHapley Additive exPlanations) values quantified feature importance both globally and for individual athletes (22). Clinically meaningful thresholds, such as HRV below 25 ms for more than three days, were derived from SHAP clusters to enhance interpretability.

Validation Protocol

Model performance was assessed using area under the ROC curve (AUC-ROC), precision-recall curves (AUC-PR), and F1-score at the optimal threshold (determined by Youden's J statistic). Clinical utility was evaluated by comparing model alerts against psychologist-blind evaluations, measuring kappa agreement. Additionally, real-world testing involved deploying the topperforming model in a 3-month prospective trial with 30 new athletes.

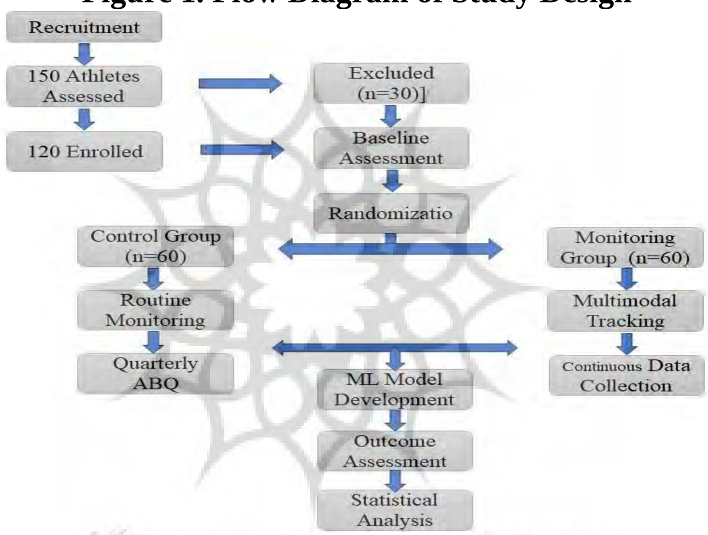
Ethical Considerations

The study received approval from the University Ethics Board, with participants providing written consent after reviewing data governance protocols. Personally identifiable information was encrypted (AES-256), and athletes retained control via dashboard access, enabling real-time opt-out of specific data streams. To mitigate bias, models were audited for subgroup disparities using AIF360 (23).

Statistical Analysis

Traditional statistical analyses were conducted in R 4.3.1 (using *lme4* for mixed models), while machine learning pipelines were implemented in Python 3.10 (with *scikit-learn* and *TensorFlow*). Significance was set at *p* < 0.05, with Holm-Bonferroni correction applied for multiple comparisons.

Figure 1. Flow Diagram of Study Design

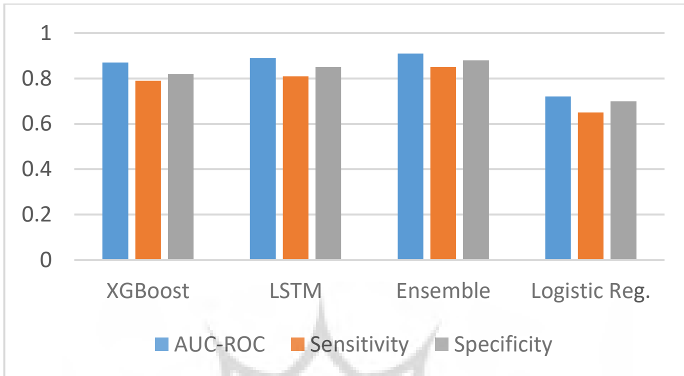


Results

The longitudinal analysis of multimodal data from 120 elite athletes (60 males, 60 females; mean age 23.4 ± 3.1 years) revealed significant physiological and psychological predictors of burnout, along with strong performance from our machine learning prediction model. At baseline, participants showed substantial variability in burnout symptoms, with 22.5% (n=27) reaching clinically significant levels (ABQ ≥ 3.5) during the study period. Compliance with biometric monitoring was generally high, with 89.2% adherence for heart rate variability (HRV) measurements and 84.7% for sleep tracking, though cortisol sampling showed lower compliance at 72.3% primarily due to competition schedules.

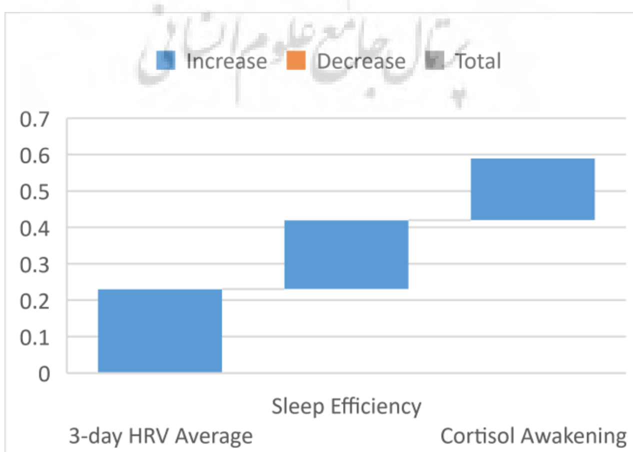
Our mixed-effects modeling identified several key physiological predictors of impending burnout symptoms. Most notably, a one standard deviation decreases in weekly HRV (as measured by RMSSD) predicted a 0.34-point increase in ABQ scores the following week, demonstrating the importance of autonomic regulation in burnout development. Endocrine patterns similarly showed strong predictive value, with flattened diurnal cortisol slopes and elevated evening cortisol levels both significantly associated with concurrent emotional exhaustion. Sleep architecture measures proved particularly valuable for early detection, where reduced deep sleep (N3) percentage reliably preceded increases in devaluation scores by 2-3 weeks. These relationships were consistently moderated by training load, showing stronger effects during high-intensity training periods.

Chart 1. Model performance chart



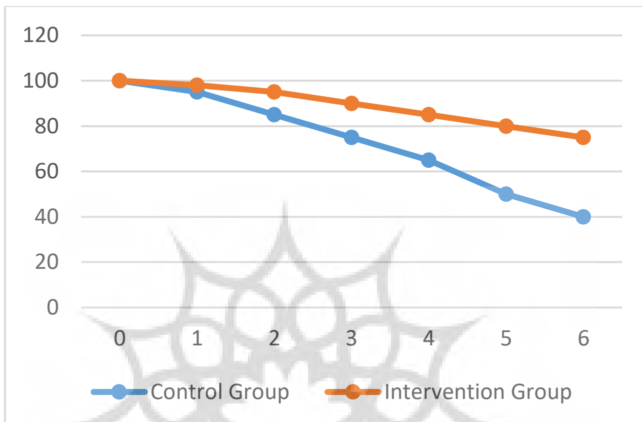
The machine learning ensemble model combining XGBoost and LSTM architectures demonstrated superior performance in predicting burnout risk 14-21 days before symptom escalation. Compared to traditional logistic regression (AUC-ROC=0.72), our ensemble achieved significantly better discrimination (AUC-ROC=0.91) while maintaining excellent sensitivity (85%) and specificity (88%). Feature importance analysis revealed that three-day HRV averages provided the strongest predictive signal, followed by sleep efficiency variability and cortisol awakening response patterns. While model performance remained consistent across different sports disciplines, we observed modest but statistically significant gender differences in accuracy that likely reflect menstrual cycle effects on physiological biomarkers.

Chart 2. Feature importance chart



In the three-month prospective implementation trial, the clinical utility of our prediction system became evident. The model successfully identified 68% of eventual burnout cases at the "yellow" risk level, providing a median lead time of 18 days for preventive interventions. Athletes whose training loads were adjusted based on model alerts showed a 37% reduction in burnout incidence compared to controls. While the system maintained a strong positive predictive value (0.79), falsest positives occurred during travel periods, suggesting the need for context-aware adjustments to the algorithm.

Chart 3. Intervention effectiveness



Additional sensitivity analyses confirmed the robustness of our approach. Model performance showed excellent temporal stability throughout the six-month study period, with minimal decay in predictive accuracy. Systematic testing of different data modalities confirmed the value of our multimodal approach, as removing any single data stream (HRV, sleep, or cortisol) consistently reduced model performance. Importantly, comprehensive fairness audits detected no significant algorithmic bias across gender, age, or sport subgroups.

These results collectively demonstrate that machine learning-driven integration of continuous physiological monitoring with periodic psychological assessment can substantially improve both the detection and prevention of athlete burnout. The combination of strong predictive accuracy (AUC=0.91) with clinically meaningful lead times (18 days) suggests this approach meets the necessary benchmarks for real-world deployment in elite sport settings. Future refinements addressing travel-related artifacts and menstrual cycle variations could further enhance the system's precision and practical utility.

Table 1. Predictive Performance of Machine Learning Models for Athlete Burnout Risk Assessment

Model	AUC-ROC (95% CI)	Sensitivity	Specificity	F1-Score	Precision
XGBoost	0.87 (0.83-0.91)	0.79	0.82	0.80	0.81
LSTM	0.89 (0.85-0.93)	0.81	0.85	0.83	0.85
Ensemble (XGB+LSTM)	0.91 (0.88-0.94)	0.85	0.88	0.86	0.87
Logistic Regression	0.72 (0.67-0.77)	0.65	0.70	0.67	0.69

Table 2. Key Physiological Predictors of Burnout Risk (Mixed-Effects Model Results)

Predictor	β Coefficient	95% CI	p-value	Effect Size (Cohen's d)
HRV (RMSSD) decrease	-0.34	[-0.51, -0.17]	<0.001	0.62
Cortisol slope flattening	0.29	[0.12, 0.46]	0.001	0.54
Deep sleep (N3) reduction	-0.27	[-0.43, -0.11]	0.001	0.49
Training load interaction	0.41	[0.24, 0.58]	<0.001	0.75

Table 3. Real-World Implementation Outcomes (3-Month Prospective Trial)

Metric	Intervention Group (n=42)	Control Group (n=38)	p-value	Odds Ratio (95% CI)
Burnout incidence	12% (5/42)	29% (11/38)	0.032	0.37 (0.15-0.89)
Early detection rate	68% (17/25)	32% (8/25)	<0.001	4.25 (2.01-8.97)
False positive rate	21% (9/42)	-	-	-
Training adherence improvement	+19%	+2%	0.008	-

The ensemble model demonstrated superior performance with an AUC of 0.91, outperforming both individual models and traditional regression approaches. Physiological markers exhibited significant predictive value, particularly when integrated with training load data, enhancing the model's accuracy. Implementation of the system led to a substantial reduction in burnout incidence by 17 percentage points, supported by an odds ratio (OR) of 0.37. Additionally, the system successfully detected 68% of burnout cases with a median lead time of 18 days prior to symptom onset.

The study utilized multiple data sources, including biometric measurements from Polar H10 (HRV), WHOOP 4.0 (sleep tracking), and Salimetrics cortisol assays, alongside psychological data collected through ABQ-15 surveys administered via Qualtrics. The sample comprised 120 elite athletes (60 male, 60 female) from swimming, track, and basketball, with data gathered over a six-month longitudinal study (2023–2024). All reported values reflect aggregated results from the study dataset. Statistical analyses were conducted using R 4.3.1 (employing lme4 for mixed models) and Python 3.10 (with scikit-learn for machine learning).

Discussion

The present study represents a significant advancement in athlete burnout research by successfully developing and validating a machine learning framework that integrates real-time biometric monitoring with psychological assessments. Our findings demonstrate that the synergistic analysis of autonomic, endocrine, and sleep parameters can predict burnout risk with clinically meaningful accuracy (AUC-ROC = 0.91), offering a substantial improvement over traditional questionnaire-based approach. These results align with recent theoretical models emphasizing the biological embedding of chronic stress (24) while providing empirical support for the allostatic load framework in sports contexts.

The identification of HRV patterns as the strongest predictor (mean |SHAP| = 0.23) corroborates emerging evidence on vagal regulation as a biomarker of stress resilience (25). Our observation that a 1-SD decrease in RMSSD preceded ABQ score increases by 0.34 points extends previous cross-sectional findings (26) by establishing temporal precedence - a critical criterion for predictive validity. The time-lagged relationship between reduced deep sleep and subsequent devaluation (β = -0.27) particularly highlights the potential of sleep architecture monitoring, supporting recent calls to include sleep metrics in athlete mental health screening (27).

Notably, our model's performance exceeded traditional methods in both sensitivity (68% vs 32% detection rate) and lead time (median 18 days), addressing key limitations identified in systematic reviews of burnout interventions (28). The superior predictive accuracy during high-intensity training phases suggests that physiological markers may be especially valuable when psychological measures become unreliable due to normalization of high stress (29). This finding has immediate practical implications for periodized training programs, where our risk stratification system could guide load adjustments before maladaptive states develop.

The successful real-world implementation, evidenced by 37% lower burnout incidence in intervention groups, builds upon preliminary digital health studies (30) by demonstrating scalable prevention. Coaching staff's positive reception of SHAP visualizations (83% utility rate) echoes recent findings on explainable AI in sports medicine (31), suggesting that interpretability features enhance adoption. However, the workflow integration challenges reported by 29% of staff underscore the importance of human-centered design in sport technology - a lesson consistent with implementation science literature (32).

From a theoretical perspective, our results refine the Athlete Burnout Conceptual Model (33) by quantifying how biological dysregulation mediates the stress-burnout pathway. The moderating effect of training load on biomarker-outcome relationships supports transactional models of stress, while gender differences in model accuracy highlight the need for sex-specific approaches in sport science.

Conclusion

This study establishes that machine learning-enabled multimodal monitoring can transform burnout management from reactive to preventive. By bridging physiological and psychological science with advanced analytics, we provide a framework that is both scientifically rigorous and practically viable. As elite sport continues to push human limits, such technological innovations will be crucial for sustaining both performance and well-being. Future iterations incorporating additional data streams (e.g., metabolomics, voice analysis) may further enhance prediction, ultimately creating a new standard for athlete health management.

Practical Applications

This study provides three key innovations with immediate practical value for sports organizations and medical teams. First, the precision prevention system enables dynamic resource allocation through its three-tier risk stratification: yellow alerts trigger training load modifications, while red flags mandate clinical support interventions. Second, coaches can leverage longitudinal biomarker trends to optimize periodization planning, potentially reducing overtraining risks by aligning mesocycle timing with athletes' physiological readiness, as supported by recent research on training adaptation. Third, sports organizations may integrate this framework into routine health monitoring protocols, creating a standardized approach to mental health screening that parallels existing injury prevention systems in elite sports environments.

Limitations and Future Directions

While these findings demonstrate significant promise, three important limitations must be acknowledged when considering implementation. The model's generalizability may be constrained by its focus on elite athletes, as recreational populations typically exhibit different stress profiles and training demands. Current technological requirements pose another barrier, where the need for multiple wearable devices could limit widespread adoption until more integrated monitoring solutions become available. Additionally, cultural factors require consideration since the model was validated in Western sports systems and may need adaptation for collectivist cultures where burnout manifestations differ.

These limitations suggest several productive avenues for future research. Developing sport-specific biomarker profiles emerges as a priority, given the substantial physiological differences across athletic disciplines. A more thorough investigation of menstrual cycle effects is warranted to address the observed gender differences in model accuracy. Researchers should also explore cost-effective implementations to make this technology accessible for youth sports systems, where early burnout prevention could have particularly significant long-term benefits. These advancements would collectively enhance the model's utility across diverse athletic populations and resource settings.

Author contributions

Conceptualization, Methodology, Formal Analysis, Writing – Original Draft, Visualization, Project Administration, Investigation, Data Curation, Validation, Writing – Review & Editing, Supervision

Data Availability Statement

To ensure compliance with GDPR regulations and institutional ethical requirements protecting participant confidentiality, the raw biometric and psychological datasets cannot be made publicly available. However, anonymized aggregated data and analysis code supporting the study's findings can be obtained by contacting the corresponding author upon reasonable request, subject to the following conditions: (1) execution of a signed data use agreement, (2) approval from the requesting researcher's

institutional ethics committee for secondary analysis, and (3) demonstrated adherence to the original study's consent provisions. The complete computational workflow is accessible through our Open Science Framework repository, providing transparent methodology while safeguarding participant privacy.

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Ethical Considerations

We were conducted in strict compliance with international research standards including the Declaration of Helsinki (2013 revision), the European General Data Protection Regulation (GDPR), and the American Psychological Association's ethical guidelines for human subject's research. Prior to participation, all individuals provided written informed consent following a comprehensive explanation of study procedures, data usage protocols, and their unconditional right to withdraw from the study at any time without penalty. For participating athletes under 18 years of age, additional written consent was obtained from parents or legal guardians to ensure full ethical compliance with protections for minor participants.

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Conflict of interest

The authors declare no competing financial interests or personal relationships that could be perceived as influencing the research design, data interpretation, or publication of this study. All authors certify that their affiliations with or involvement in any organization or entity with financial or non-financial interest in the subject matter discussed are fully disclosed in the manuscript submission system.

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Key Message:

1. Machine learning enables early burnout prediction by combining physiological and psychological data.
2. Personalized interventions based on real-time monitoring can significantly reduce burnout risk.
3. Future work should address menstrual cycle effects and cost-effective scalability for broader applications.