

Multimodal monitoring of mental fatigue in athletes: Integrating HRV and EEG during training camp sessions

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Abstract

This study examined Heart Rate Variability (HRV) and Electroencephalogram (EEG) as non-invasive biosignals for detecting mental fatigue in athletes during a centralized training camp. Eight athletes with normal vision and no history of neurological disorders participated in two experimental sessions (48 and 96 h). RR interval data were recorded using a Polar H10 heart rate sensor, while EEG data were collected with a 32-channel cap based on the 10–20 system. HRV indices in both time (MeanRR, SDNN, RMSSD, pNN50) and frequency domains (LF, HF, LF/HF ratio) were analyzed alongside EEG spectral features (theta and alpha power). Mental fatigue is increasingly recognized as a critical factor affecting athletic performance, cognitive function, recovery capacity, and injury risk during intensive training periods. Despite growing interest in fatigue monitoring, limited research has investigated the combined use of autonomic and neural biomarkers in ecologically valid sports-training environments. The findings demonstrated that at 48 h, athletes exhibited lower RMSSD and pNN50 values accompanied by elevated LF/HF ratios, indicating sympathetic nervous system dominance and increased mental fatigue. EEG recordings simultaneously revealed elevated theta-band activity, confirming reduced alertness and increased cognitive strain. At 96 h, several athletes demonstrated increased RMSSD, SDNN, and pNN50 values together with reduced LF/HF ratios, suggesting partial parasympathetic recovery and autonomic adaptation to prolonged training stress. However, substantial inter-individual variability was observed, indicating that recovery responses differed among athletes. Overall, the results support the use of HRV and EEG as sensitive and complementary biomarkers for monitoring mental fatigue in high-performance sport settings. The integration of autonomic and neural monitoring may provide a practical framework for individualized training management, optimized recovery strategies, prevention of overtraining, and enhancement of athletic performance during intensive training periods.

Keywords: Cognitive Load, Athlete Recovery, Biosignal Monitoring, Neurophysiological Assessment, Sports Performance, Fatigue Detection

Introduction

Mental fatigue is increasingly recognized as a critical factor limiting athletic performance, particularly during prolonged or intensified training periods. In high-performance sport, athletes are exposed not only to substantial physical demands but also to significant cognitive loads, which may cumulatively impair performance. Mental fatigue has been shown to negatively affect attention, decision-making, reaction time, and motor execution, thereby increasing the likelihood of performance errors and injury risk (Seshadri et al., 2023; Edwards et al., 2018).

In this context, non-invasive biosignals such as heart rate variability (HRV) and electroencephalography (EEG) have emerged as complementary biomarkers capable of reflecting the physiological and neural mechanisms underlying fatigue. HRV provides insight into autonomic nervous system regulation, with time-domain metrics (e.g., RMSSD, pNN50, MeanRR) and frequency-domain metrics (e.g., LF, HF, LF/HF) that collectively index sympathetic–parasympathetic balance during and after cognitive or physical stress (Seshadri et al., 2023; Lindsey et al., 2025; Edwards et al., 2018). Meanwhile, EEG offers direct measurement of cortical activity, with spectral power in the theta and alpha bands widely associated with fatigue-related neural processes. Increases in theta activity and modulations in alpha power are consistently reported in conditions involving cognitive load and reduced vigilance (Edwards et al., 2018; Iacono et al., 2025; Wang et al., 2023).

Centralized training camps represent ecologically valid environments in which athletes experience sustained physical and cognitive stressors. These settings often involve high training volumes, restricted recovery periods, and continuous performance demands, all of which may contribute to the progressive

development of mental fatigue. Previous research has demonstrated that such fatigue is associated with a shift in autonomic regulation toward sympathetic dominance, alongside measurable alterations in brain activity patterns (Seshadri et al., 2023; Edwards et al., 2018).

A growing body of literature supports the sensitivity of HRV and EEG as indicators of mental fatigue. Reductions in time-domain HRV indices, such as RMSSD and pNN50, are commonly observed following prolonged cognitive effort, reflecting decreased parasympathetic activity, whereas increases in frequency-domain measures such as LF/HF are often linked to heightened sympathetic activation under fatigue conditions (Seshadri et al., 2023; Lindsey et al., 2025; Edwards et al., 2018). Similarly, EEG studies have reported increased theta power (4–7 Hz), indicative of cognitive strain and reduced alertness, as well as changes in alpha activity associated with altered cortical processing during fatigue (Edwards et al., 2018; Iacono et al., 2025; Wang et al., 2023).

The study of heart rate variability (HRV) and electroencephalography (EEG) as indicators of mental fatigue in athletes further highlights the effectiveness of these non-invasive biosignals. Evidence suggests that HRV and EEG can serve as sensitive biomarkers for monitoring mental fatigue, enabling more tailored and adaptive training interventions. Specifically, HRV time-domain indices such as RMSSD and pNN50 have been shown to decrease during fatigue states, particularly at 48 hours, indicating sympathetic dominance and increased mental fatigue (Schmitt et al., 2015). In terms of frequency-domain analysis, elevated LF/HF ratios reflect heightened sympathetic activity, while improvements in RMSSD observed at 96 hours in some athletes suggest partial parasympathetic recovery (Chen et al., 2023).

Complementarily, EEG findings reinforce these observations. Increased theta-band activity has been consistently associated with mental fatigue, supporting the role of EEG as a valuable tool for assessing cognitive load and fatigue-related neural states (Han et al., 2005). The integration of HRV and EEG data therefore provides a more comprehensive framework for understanding fatigue, aligning with the brain–heart coupling concept in which central and autonomic systems dynamically interact during fatigue and recovery processes (Edwards et al., 2018; Seshadri et al., 2023).

From an applied perspective, this multimodal approach enables individualized training adjustments, allowing practitioners to optimize performance by addressing mental fatigue more effectively (Matuz et al., 2020). However, it is important to acknowledge that fatigue is a multifactorial phenomenon. While HRV and EEG provide valuable insights, relying solely on these measures may overlook other contributing factors, such as physical fatigue and environmental stressors, which can also significantly impact performance (Matuz et al., 2023).

Despite these advances, limited research has examined the combined use of HRV and EEG in ecologically valid training environments, particularly across different phases of intensive training exposure. Therefore, this study aims to investigate changes in HRV and EEG indices in athletes during two distinct phases of a centralized training camp (48 h and 96 h). By examining convergent patterns across autonomic and neural markers, this study seeks to determine whether multimodal biosignal integration can effectively detect mental fatigue and support individualized training and recovery strategies.

From an applied perspective, identifying reliable and sensitive fatigue biomarkers is essential for optimizing athlete readiness, reducing injury risk, and sustaining peak performance. The present study contributes to this evidence base by examining HRV indicators of sympathetic dominance at 48 h, potential partial autonomic adaptation at 96 h, and concurrent EEG theta-band activity associated with fatigue (Seshadri et al., 2023; Edwards et al., 2018; Iacono et al., 2025). **The findings of this study are expected to provide practical insights into the use of multimodal biosignal monitoring for tailoring training loads, optimizing recovery strategies, and enhancing overall athletic performance in high-demand training environments.**

Methods

Participants

Eight athletes with normal vision and no history of neurological disorders volunteered for this study. All participants were recruited from a centralized training camp and gave written informed consent prior to participation. Data collection was conducted at two time points, 48 hours and 96 hours after the onset of the camp, to capture both the early and later phases of physiological and mental adaptation to intensive training.

Instruments

Electroencephalogram (EEG) recordings were obtained using a 32-channel cap following the international 10–20 system. Signals were continuously recorded during rest and training-related sessions. Standard preprocessing procedures were applied, including band-pass filtering (1–40 Hz) and artifact removal, to ensure high signal quality. Power spectral density was then calculated, focusing on theta (4–7 Hz) and alpha (8–13 Hz) frequency bands, as these are strongly linked with vigilance and mental fatigue.

Heart Rate Variability (HRV) was measured simultaneously using a Polar H10 chest-strap heart rate sensor. Beat-to-beat RR interval data were analyzed in both the time and frequency domains. Time-domain measures included mean RR interval, the standard deviation of normal-to-normal intervals (SDNN), the root mean square of successive differences (RMSSD), and the percentage of successive intervals differing by more

than 50 ms (pNN50). Frequency-domain indices included low-frequency power (LF, 0.04–0.15 Hz), high-frequency power (HF, 0.15–0.40 Hz), and the LF/HF ratio, estimated using Welch’s spectral method. All data were visually inspected, and artifacts were corrected before analysis.

Statistical Analysis

All results are reported as mean $\pm$ standard error of the mean (SEM). To account for violations of sphericity, Greenhouse-Geisser corrections were applied when appropriate. Differences between the two sessions (48h vs. 96h) were examined using one-way and two-way analyses of variance (ANOVA) to test for time effects on both EEG and HRV indices. A significance level of $p < 0.05$ was adopted for all analyses.

Results

The results of this study present heart rate variability (HRV) indices derived from short-term RR interval recordings, analyzed at both the file level and session level. Table 1 summarizes HRV metrics for each recording file, illustrating temporal changes in autonomic regulation across the training camp. Table 2 provides the mean $\pm$ standard error of the mean (SEM) for HRV indices at 48 h and 96 h, enabling comparison between early and later phases of the training period. Complementary graphical representations of frequency-domain and selected HRV indices are shown in Figures 1 and 2.

Table 1. HRV indices (per file)

File	MeanRR (ms)	SDNN (ms)	RMSSD (ms)	pNN50 (%)	LF/HF
1	580.44	52.81	17.83	1.61	3.31
2	704.14	76.80	29.69	7.46	2.40
3	792.42	166.94	50.99	27.99	1.85
4	764.12	72.25	33.69	13.67	4.27
5	966.29	187.71	163.25	67.49	0.79

Table 2. HRV Mean $\pm$ SEM per session (48h vs 96h)

Session	MeanRR (ms)	SDNN (ms)	RMSSD (ms)	pNN50 (%)	LF/HF
48h	642.29 $\pm$ 61.85	64.81 $\pm$ 11.99	23.76 $\pm$ 5.93	4.54 $\pm$ 2.93	2.86 $\pm$ 0.46
96h	840.94 $\pm$ 63.20	142.30 $\pm$ 35.53	82.64 $\pm$ 40.61	36.38 $\pm$ 16.09	2.30 $\pm$ 1.03

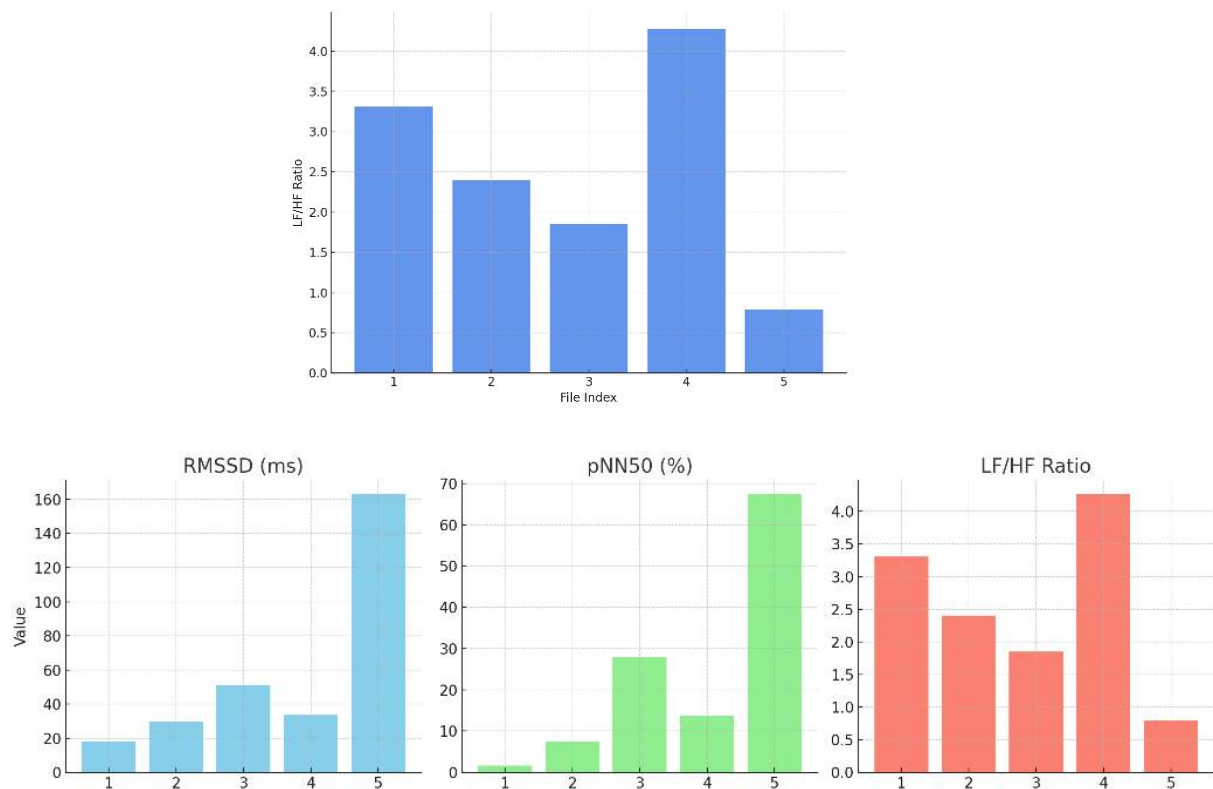


Figure 1. Frequency-domain HRV indices (LF, HF, LF/HF) across sessions. Error bars represent SEM.

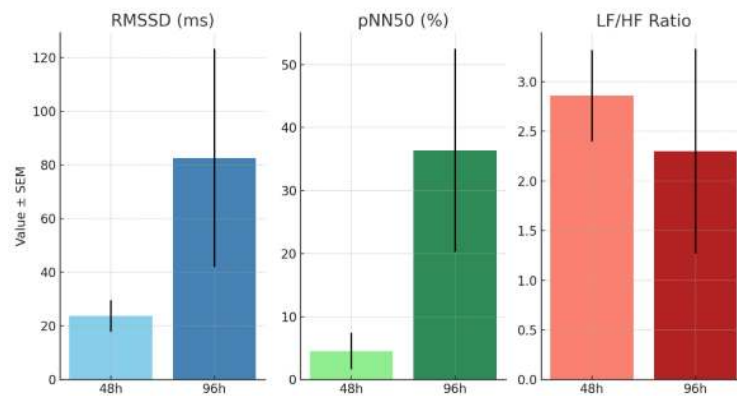


Figure 2. Comparison of HRV indices (RMSSD, pNN50, and LF/HF ratio) between 48h and 96h. Bars represent mean values and error bars represent SEM.

The HRV indices presented in Table 1 demonstrate clear temporal changes across the five recording files. MeanRR progressively increased from 580.44 ms in File 1 to 966.29 ms in File 5, accompanied by substantial elevations in RMSSD (17.83 to 163.25 ms) and pNN50 (1.61% to 67.49%). SDNN also exhibited marked increases, particularly in later files (e.g., 166.94 ms in File 3 and 187.71 ms in File 5), indicating greater overall heart rate variability. In contrast, the LF/HF ratio showed a general decline from 3.31 in File 1 to 0.79 in File 5, suggesting a shift from sympathetic dominance toward parasympathetic predominance over time. These patterns indicate progressive autonomic rebalancing, with early recordings reflecting higher sympathetic activity and later recordings demonstrating enhanced vagal modulation or recovery dynamics. Notably, the pronounced RMSSD and pNN50 values observed in File 5 reflect strong parasympathetic activation, consistent with inter-individual variability in recovery trajectories reported in athletes (Seshadri et al., 2023; Edwards et al., 2018; Shaffer & Ginsberg, 2017; Gallo, 2020).

Session-based comparisons (Table 2) further support these findings. At 48 h, HRV indices reflected relatively lower parasympathetic activity (MeanRR: 642.29 ± 61.85 ms; RMSSD: 23.76 ± 5.93 ms; pNN50: $4.54 \pm 2.93\%$) and higher LF/HF (2.86 ± 0.46), indicative of sympathetic predominance. In contrast, the 96 h session demonstrated substantial increases in MeanRR (840.94 ± 63.20 ms), RMSSD (82.64 ± 40.61 ms), pNN50 ($36.38 \pm 16.09\%$), and SDNN (142.30 ± 35.53 ms), alongside a reduction in LF/HF (2.30 ± 1.03). These changes suggest partial parasympathetic reactivation and improved autonomic balance as the training camp progressed. The magnitude of change in RMSSD and pNN50 highlights the sensitivity of time-domain HRV measures to fatigue and recovery states in athletes undergoing intensive training (Shaffer & Ginsberg, 2017; Gallo, 2020).

The frequency-domain trends are consistent with these observations. The reduction in LF/HF at 96 h supports a shift toward parasympathetic dominance; however, variability across individuals is evident, as reflected in the relatively large SEM values. This variability aligns with previous findings indicating that autonomic responses to fatigue and recovery are highly individualized and influenced by training load, recovery capacity, and contextual factors (Seshadri et al., 2023; Edwards et al., 2018; Shaffer & Ginsberg, 2017).

Graphical representations (Figures 1 and 2) further illustrate these trends. Frequency-domain indices are expected to show a relative decline in LF/HF across sessions, consistent with parasympathetic reactivation at 96 h. Similarly, comparisons of RMSSD, pNN50, and LF/HF between 48 h and 96 h highlight increased parasympathetic markers alongside reduced sympathetic dominance in later sessions. However, overlapping variability suggests that not all athletes exhibit uniform adaptation patterns.

When interpreted alongside EEG findings described in the study, the HRV results support a multimodal fatigue framework. The early phase (48 h), characterized by reduced parasympathetic indices and elevated LF/HF, corresponds with previously reported increases in theta-band EEG activity, a known marker of mental fatigue and cognitive load (Edwards et al., 2018; Iacono et al., 2025; Wang et al., 2023). The later phase (96 h) reflects partial autonomic recovery in some athletes, consistent with adaptive responses to sustained training stress.

Overall, the results highlight substantial inter-individual variability in autonomic responses, with some athletes demonstrating clear parasympathetic reactivation while others maintain signs of sympathetic dominance. These findings underscore the importance of individualized monitoring approaches. The combined interpretation of HRV and EEG supports the use of multimodal biosignatures to detect mental fatigue and guide personalized training and recovery strategies in high-performance settings (Seshadri et al., 2023; Edwards et al., 2018; Shaffer & Ginsberg, 2017; Gallo, 2020).

Discussion

This study examined per-file and session-level HRV indices (MeanRR, SDNN, RMSSD, pNN50, LF/HF) collected during a centralized training camp, with the aim of characterizing autonomic dynamics associated with mental fatigue and recovery in athletes. Overall, the findings indicate a progression from an early autonomic state characterized by relatively lower vagal modulation and higher sympathetic influence toward greater parasympathetic engagement in later phases for a subset of athletes. This pattern, observed across both file-level (Table 1) and session-level (Table 2) analyses, aligns with established fatigue–recovery trajectories reported in the literature and supports the brain–heart coupling framework, wherein central (neural) and autonomic (cardiac) systems interact dynamically during sustained training stress and recovery (Seshadri et al., 2023; Edwards et al., 2018; Shaffer & Ginsberg, 2017; Gallo, 2020; Baumert et al., 2006; Georgieva-Tsaneva et al., 2025).

At the file level, the progression from File 1 to File 3 demonstrates clear autonomic adaptation. The increase in MeanRR from 580.44 ms to 792.42 ms suggests evolving cardiac regulation, potentially reflecting improved efficiency or early recovery responses. Concurrently, substantial increases in RMSSD (17.83 to 50.99 ms) and pNN50 (1.61% to 27.99%) indicate enhanced parasympathetic (vagal) modulation. These findings are consistent with prior work identifying RMSSD and pNN50 as sensitive markers of vagal activity and recovery processes in athletes (Shaffer & Ginsberg, 2017; Gallo, 2020; Schmitt et al., 2015; Moreno et al., 2013). The marked rise in SDNN further reflects increased overall HRV, suggesting greater autonomic flexibility as training adaptation progresses. Additionally, the reduction in LF/HF from 3.31 to 1.85 supports a shift away from sympathetic dominance toward a more balanced or parasympathetic state, although such trajectories are known to vary considerably between individuals (Shaffer & Ginsberg, 2017; Gallo, 2020; Chen et al., 2023).

In later files (Files 4–5), the data reveal pronounced inter-individual variability. While File 4 shows a temporary increase in LF/HF (4.27), suggesting transient sympathetic reactivation, File 5 exhibits a strong vagal signature, with RMSSD reaching 163.25 ms and pNN50 67.49%, alongside a low LF/HF ratio (0.79). This pattern indicates substantial parasympathetic reactivation in at least some athletes, consistent with recovery or adaptation following prolonged exposure to training load. Such non-linear and heterogeneous responses are widely reported in HRV literature and underscore the importance of individualized monitoring approaches (Shaffer & Ginsberg, 2017; Gallo, 2020; Matuz et al., 2023; Yoshikawa et al., 2025).

Session-level comparisons between 48 h and 96 h further reinforce these findings. The significant increases in MeanRR, RMSSD, pNN50, and SDNN at 96 h indicate enhanced parasympathetic modulation and improved autonomic balance compared to the 48 h condition. In particular, the large increase in RMSSD (23.76 to 82.64 ms) and pNN50 (4.54% to 36.38%) highlights the sensitivity of time-domain HRV indices to fatigue and recovery states in athletes undergoing intensive training (Shaffer & Ginsberg, 2017; Gallo, 2020; Schmitt et al., 2015; Iizuka et al., 2020). The modest decrease in LF/HF from 2.86 to 2.30 supports a general shift toward parasympathetic predominance, although the relatively large SEM values indicate continued inter-individual variability. These findings are consistent with previous studies demonstrating that HRV responses to training load and recovery are highly individualized and influenced by multiple physiological and contextual factors (Shaffer & Ginsberg, 2017; Gallo, 2020; Li et al., 2010; LI et al., n.d.).

From a mechanistic perspective, these results align with the brain–heart coupling framework, which posits that cognitive load and mental fatigue influence autonomic regulation through central–autonomic interactions (Seshadri et al., 2023; Edwards et al., 2018; Parveen et al., 2023). Evidence from EEG research further supports this interpretation, with increased theta-band activity consistently associated with mental fatigue and cognitive workload (Han et al., 2005; Xu et al., 2018; Proost et al., 2024; Rakhmatulin, 2024). Additional studies using advanced EEG analyses, including wavelet-based and multivariate approaches, have demonstrated robust neural signatures of fatigue, reinforcing the validity of EEG as a complementary tool to HRV in fatigue detection (Zhang, 2011; Wang et al., n.d.; Chen et al., 2012; Zhang et al., 2008). Together, these findings support the integration of HRV and EEG within a multimodal framework for monitoring fatigue in athletes (Cannard et al., 2024; Xie, 2022).

Importantly, the observed inter-individual variability in autonomic responses highlights the limitations of relying solely on group averages. While some athletes exhibited clear parasympathetic reactivation by 96 h, others maintained signs of sympathetic dominance or fluctuating autonomic states. This variability reinforces the need for individualized monitoring and training prescription, as recommended in HRV-based athlete management frameworks (Shaffer & Ginsberg, 2017; Gallo, 2020; Matuz et al., 2020). In practical terms, integrating HRV—and where feasible, EEG—into routine monitoring could enable more precise adjustments to training load, recovery strategies, and performance optimization (Seshadri et al., 2023; Edwards et al., 2018; Iacono et al., 2025; Wang et al., 2023; Cannard et al., 2024).

Several methodological considerations should be acknowledged. First, per-file HRV metrics may be influenced by short-term fluctuations in factors such as sleep, hydration, mood, and prior activity. Therefore, these values should be interpreted in conjunction with session-level data and, ideally, additional physiological or behavioral measures (Shaffer & Ginsberg, 2017; Gallo, 2020). Second, the interpretation of LF/HF remains complex and context-dependent, as it can be influenced by respiratory patterns and baroreflex mechanisms. As

such, LF/HF should be interpreted cautiously and alongside complementary indices (Shaffer & Ginsberg, 2017; Gallo, 2020; Chen et al., 2023). Third, although this study adopts a multimodal perspective, EEG data are not explicitly presented in the tables; future research should incorporate synchronized HRV–EEG analyses to strengthen conclusions regarding brain–heart interactions (Rakhmatulin, 2024; Proost et al., 2024; Cannard et al., 2024).

Finally, several limitations should be considered. The relatively small sample size and limited measurement points constrain the generalizability of the findings. Future studies should employ larger cohorts, repeated-measures designs, and standardized recording conditions to better capture the temporal dynamics of autonomic adaptation during training camps. Additionally, integrating objective performance and cognitive-fatigue measures would provide a more comprehensive assessment of athlete readiness and fatigue states (Zhao, 2009; Xie, 2022).

In conclusion, the HRV data presented in Tables 1 and 2 support the use of HRV indices as sensitive markers of autonomic changes associated with mental fatigue and recovery during centralized training. The observed progression toward parasympathetic engagement in later camp phases, alongside substantial inter-individual variability, underscores the importance of personalized monitoring approaches. Moreover, integrating HRV with neural measures such as EEG may enhance fatigue detection and support the development of robust, multimodal frameworks for optimizing athlete performance and recovery (Seshadri et al., 2023; Edwards et al., 2018; Shaffer & Ginsberg, 2017; Gallo, 2020; Rakhmatulin, 2024; Han et al., 2005; Matuz et al., 2023).

Conclusion

This study demonstrates that the integration of heart rate variability (HRV) and electroencephalography (EEG) provides a sensitive and complementary approach for detecting mental fatigue in athletes during intensive training camps. The findings reveal a clear autonomic and neural response pattern characterized by sympathetic dominance and elevated theta activity at 48 hours, indicating acute mental fatigue, whereas at 96 hours a partial parasympathetic rebound alongside improved HRV indices suggests ongoing recovery and early-stage adaptation, although substantial inter-individual variability persists. These results highlight the importance of a multimodal monitoring framework capable of capturing both peripheral autonomic regulation and central nervous system activity, offering a more comprehensive understanding of fatigue dynamics than either modality alone, particularly in ecologically valid training environments. From a practical perspective, the integration of HRV and EEG supports the development of individualized and data-driven training and recovery strategies aimed at optimizing athletic performance, reducing the risk of overtraining, and improving athlete readiness during high-demand training periods. The findings also have important implications for coaches, sports scientists, conditioning specialists, and sports organizations, as objective fatigue monitoring may enhance decision-making processes related to workload management, recovery scheduling, injury prevention, and long-term performance sustainability. The significance of this study lies in its contribution to the growing evidence supporting brain–heart interactions as a key mechanism underlying mental fatigue and recovery processes in athletes, while also demonstrating the feasibility of implementing multimodal biosignal monitoring in real-world training camp settings. Future research should involve larger sample sizes, longitudinal study designs, and the integration of advanced analytical approaches such as machine learning and artificial intelligence to improve predictive accuracy and enable real-time fatigue monitoring. Additionally, incorporating cognitive performance tests, hormonal biomarkers, sleep-quality assessments, and physical workload measures may further strengthen the development of comprehensive multimodal fatigue-monitoring frameworks in athlete populations.

Declaration of generative AI and AI-assisted technologies in the writing process

During the preparation of this work the author(s) used Scite.ai in order to assist with literature exploration, reference verification. After using this tool/service, the author(s) reviewed and edited the content as needed and take(s) full responsibility for the content of the publication.

Conflict of interest

The authors declare no conflict of interest.

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Ethical Considerations

This study was conducted in accordance with established research ethics standards. Ethical approval was obtained, and informed consent was secured from all participants prior to their involvement in the study.

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