

Multidimensional Monitoring of Recovery States, Biomarkers, Workload, and Performance in Elite Basketball: An Exploratory Longitudinal Field Study

Giulia Corazza

VitalizeDx Eu-Personalized Care

Shehneela Jamil

VitalizeDx Eu-Personalized Care <https://orcid.org/0000-0001-8369-1617>

Renis Dema

Croce Rossa Italiana Sezione di Palmanova

Sonia Zorba

VitalizeDx Eu-Personalized Care

Luca Bonetta

Pallacanestro Trieste

Anna Jòdar-Portas

University School of Health and Sport (EUSES)

Anna Prats-Puig

Research Group of Health and Health Care, Nursing Department, University of Girona

Azahara Fort-Vanmeerhaeghe

Faculty of Psychology, Education Sciences and Sport Blanquerna, Ramon Llull University

Lavinia Alberi

laviniaa@vitalizedx.com

VitalizeDx Eu-Personalized Care <https://orcid.org/0000-0002-0446-5337>

Case Report

Keywords: athlete monitoring, basketball, salivary biomarkers, recovery, workload, performance readiness, IgA

Posted Date: September 28th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-11164181/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.

[Read Full License](#)

Additional Declarations: The authors declare no competing interests.

Multidimensional Monitoring of Recovery States, Biomarkers, Workload, and Performance in Elite Basketball: An Exploratory Longitudinal Field Study

Running head: Recovery Monitoring in Elite Basketball

Authors: Giulia Corazza¹, Shehneela Jamil^{1,2}, Renis Dema^{1,3}, Sonia Zorba¹, Luca Bonetta⁴, Anna Jòdar-Portas⁵, Anna Prats-Puig⁶, Azahara Fort-Vanmeerhaeghe⁷, Lavinia Alberi^{1,8}

Affiliations:

1 VitalizeDx Eu-Personalized Care, Via Mazzini 20, 34121 Trieste (TS), Italy

2 FTPO, Ozare 19, Slovenji Gradec, 2380, Slovenia

3 Croce Rossa Italiana Sezione di Palmanova, Via Taglio, 6, 36100 Palmanova (UD), Italy.

4 Pallacanestro Trieste, Via Flavia, 3 - 34148 Trieste (TS), Italy.

5 University School of Health and Sport (EUSES), Universitat de Girona, Girona, Spain.

6 Research Group of Health and Health Care, Nursing Department, University of Girona, Girona, Spain.

7 Faculty of Psychology, Education Sciences and Sport Blanquerna, Ramon Llull University, 08022 Barcelona, Spain.

8 VitalizeDx Personalized Wellness, Route de la Corniche 5A, 1066 Epalinges, Switzerland

Corresponding Author:

Lavinia Alberi Auber

Via Riva Gulli, 12, 34123

Trieste (TS)

Email: laviniaaa@vitalizedx.com

Tel: 0041762354120

Abstract

Purpose: Elite team-sport programs increasingly combine athlete-reported wellness ratings with biochemical markers, yet the applied interpretation of these multimodal data remains uncertain. This exploratory longitudinal field study examined whether recovery-related athlete-reported states were associated with salivary markers, acute competition exposure, and performance-readiness profiles in elite basketball players.

Methods: The dataset comprised 309 observations from 13 elite basketball players monitored over 15 weeks. Athlete-reported variables included calmness, stress, anger, sleep quality, tiredness, muscle soreness, energy, and sleep duration. Salivary biomarkers included pH, uric acid, aspartate aminotransferase (AST), creatine kinase (CK), ketones, and immunoglobulin A (IgA). Minutes played were used as an indicator of acute competition exposure. Analyses included correlations and biomarker stratification, exploratory risk-enrichment analyses for biomarker abnormalities, fast-versus-slow subjective recovery comparisons, mixed-effects models of post-game-to-recovery change scores, and performance-readiness group comparisons.

Results: Severe muscle soreness and low energy were the clearest subjective flags of biomarker abnormality. The strongest enrichment was observed for low IgA among severe-soreness observations, with a rate of 75.0% compared with 14.9% among trait-negative observations. Salivary pH differentiated fast and slow recovery from tiredness ($p=0.0167$), whereas AST differentiated recovery phenotypes for energy ($p=0.0130$), calmness ($p=0.0240$), and anger ($p=0.0385$). In mixed-effects models adjusted for minutes played, tiredness change was

negatively associated with salivary pH, while anger change remained positively associated with ketones and CK. Selected associations involving tiredness and calmness also varied according to minutes played. Good- and poor-performance-readiness observations showed significantly different multivariate profiles (Wilks lambda=0.3564, $F=25.02$, $p<0.001$); good-performance-readiness observations were characterized by greater calmness, better sleep quality, higher energy, lower stress and soreness, and lower IgA concentrations.

Conclusions: Selected athlete-reported recovery and affective states were associated with distinct, although heterogeneous, salivary biomarker and performance-readiness profiles. Integrating athlete-reported measures with biomarkers and recent competition exposure may support more informed recovery and readiness decisions in elite basketball, particularly when changes are interpreted longitudinally and relative to individual athlete baselines.

Keywords: athlete monitoring; basketball; salivary biomarkers; recovery; workload; performance readiness; IgA

Key Points

- High soreness and low energy were the most consistent subjective flags of biomarker abnormality in this elite basketball dataset.
- Associations between subjective change scores and biomarkers depended partly on minutes played, supporting workload-contextualized interpretation.
- The findings are exploratory and should be used to generate hypotheses and refine monitoring protocols rather than establish diagnostic biomarker cutoffs.

1. Introduction

Elite basketball performance is produced under highly variable competitive demands, including repeated accelerations and decelerations, jumps, changes of direction, body contacts, high-intensity transitions, technical execution, and rapid tactical decision-making (1–3). These demands occur within congested training and competition schedules, often accompanied by travel, sleep disruption, nutritional constraints, and psychosocial stressors. In this context, recovery refers to the restoration of psychological, physiological, and functional capacity after training or competition, such that the athlete can tolerate subsequent load and perform effectively (4,5). When the balance between imposed stress and available recovery resources is repeatedly disrupted, athletes may develop maladaptive responses ranging from short-term functional overreaching to nonfunctional overreaching and, in severe cases, overtraining syndrome (5). Overtraining syndrome is a prolonged maladaptive condition characterized by persistent performance decrements and multisystem disturbances; however, its diagnosis remains primarily clinical because no single biomarker or universally accepted diagnostic threshold can reliably identify it (6). Accordingly, athlete monitoring should be interpreted as a strategy for identifying early patterns of inadequate recovery, excessive strain, or altered readiness rather than as a diagnostic tool for overtraining syndrome (4,7).

Contemporary athlete-monitoring systems increasingly adopt multidimensional approaches that integrate performance, physiological, psychological, and workload-related measures rather than relying on a single marker of training load, fatigue, or recovery (4,7). External workload refers to the objective work performed by the athlete, such as distance, accelerations, jumps, impacts, or, in game-based datasets, minutes played. Internal load refers to the athlete's psychophysiological response to that work, including perceived exertion, fatigue, mood, soreness, sleep disruption, autonomic responses, and biochemical changes (4,7,8). In team-sport environments, short subjective ratings are particularly valuable because they are low burden, repeatable, and feasible during competitive periods (9). In the present study, subjective psychobiophysical states are defined operationally as the combined psychological and perceived-physiological self-report variables collected from athletes, including calmness, stress, anger, sleep quality, tiredness, muscle soreness, energy, and sleep duration.

These measures may capture meaningful within-athlete fluctuations in recovery, affective state, and readiness. This is consistent with evidence indicating that self-reported measures can be sensitive to acute and chronic changes in athlete well-being and can complement objective monitoring tools (5,7,9).

Biochemical markers may provide additional information about recovery-related processes, particularly when interpreted longitudinally and within the context of workload, nutrition, illness, hydration, and individual baseline values(10,11). Salivary monitoring is attractive in applied sport settings because it is minimally invasive and can be repeated frequently (12,13). The present biomarker panel included salivary pH, uric acid, aspartate aminotransferase (AST), creatine kinase (CK), ketones, and immunoglobulin A (IgA). Salivary pH is a dimensionless measure of acidity or alkalinity in the oral fluid environment and may be influenced by salivary flow rate, hydration, oral status, diet, buffering capacity, and physiological stress (13). Uric acid is a product of purine metabolism and a major antioxidant in saliva, often interpreted in relation to redox balance, metabolic activity, and exertional stress (14). Aspartate aminotransferase and creatine kinase are enzymes commonly used as indirect markers of muscle membrane disruption or tissue stress, however, their interpretation is limited by sampling timing, muscle mass, prior exercise, and large inter-individual variability (15–17). Ketones reflect aspects of substrate availability and fat-derived energy metabolism, but salivary or strip-based ketone measures are also sensitive to nutritional timing and hydration (18–20). Immunoglobulin A is a mucosal immune protein that contributes to first-line defense on the mucosal surfaces. Salivary IgA concentration may reflect immune status, but it is also influenced by saliva flow rate, secretion rate, illness, oral health, and acute stress (21,22). Thus, although biomarkers may enhance physiological resolution to monitoring systems, they are inherently context-dependent and should not be interpreted as isolated indicators of readiness or maladaptation (10,11,23).

Despite growing interest in athlete monitoring, several gaps remain. First, many studies examine either subjective wellness or biochemical markers in isolation despite the multifactorial nature of fatigue and recovery. Accordingly, applied performance staff must interpret noisy, repeated, multidomain data collected under real-world conditions (7,9). Second, biomarker studies often use heterogeneous sampling protocols, isolated thresholds, or group-level comparisons that do not capture the individualized and longitudinal nature of athlete responses (10,11). Third, relatively little is known about whether specific subjective recovery states, such as high soreness, low energy, high anger, or persistent tiredness, are accompanied by disproportionate biomarker deviations in elite basketball (7,8). Fourth, the extent to which these associations depend on acute competition exposure remains uncertain. In basketball, minutes played provide an accessible but incomplete proxy for acute match exposure. Athletes may report similar changes in recovery or fatigue despite experiencing different levels of competition exposure; therefore, comparable subjective changes may be associated with different physiological or biochemical responses in athletes who played heavy versus limited minutes. Finally, it remains unclear whether integrated subjective-biomarker profiles differ between performance-readiness states in a way that is useful for applied monitoring.

Therefore, the main aim was to explore whether recovery-related athlete-reported psychophysical states corresponded to salivary biochemical patterns, acute competition exposure, and performance-readiness profiles in elite basketball players during a competitive season. Accordingly, the specific objectives of the study were to: (i) characterize the relationships among salivary biomarkers, athlete-reported recovery and affective states, and game-performance variables, and examine differences in biomarker distributions across levels of athlete-reported states; (ii) describe the frequency of biomarker abnormalities within prespecified high-risk athlete-reported states using risk-enrichment analyses; (iii) compare biomarker profiles between fast and slow subjective recovery phenotypes derived from post-game-to-recovery change scores; (iv) test whether subjective recovery change scores were associated with salivary biomarkers after accounting for minutes played and repeated observations within athletes; and (v) compare integrated psychobiophysical and biomarker profiles between good and poor performance-readiness observations.

2. Methods

2.1 Design and Participants

The study involved 13 elite male basketball players competing in the Italian league (Pallacanestro Trieste team), monitored over a 15-week period from January 13 to May 7, 2025. For each competitive week, data collection was performed at two timepoints relative to the game: athlete-reported psychological and physiological states were assessed post-game and again during the recovery phase (2–3 days after the match), with this two-timepoint assessment repeated weekly across the entire 15-week season, resulting in a longitudinal, repeated-measures dataset with up to two observations per athlete per week. Saliva samples were collected only during the recovery-phase assessment. Not all athletes completed both assessments in every week, because of injuries, or incomplete questionnaire or saliva sample collection; the final dataset therefore comprised fewer than the theoretical maximum number of observations. Participants were aged 30 ± 4 years (range: 20–36 years), with a body mass of $93.2 \text{ kg} \pm 8.8 \text{ kg}$ (range: 80–109 kg) and a height of $198.7 \text{ cm} \pm 9.5 \text{ cm}$ (range: 183–213 cm). All participants provided informed consent, and the study was approved by the institutional ethics review board in alignment with the WMA Declaration of Helsinki - Ethical Principles for Medical Research Involving Human Participants.

The same athlete cohort and monitoring period were previously examined using a different salivary biomarker panel and analytical framework (24). The present study addresses distinct research questions focused on recovery-related subjective states, competition exposure, and performance-readiness profiles.

2.2 Data Collection

Saliva samples were collected on recovery days (2–3 days after the match day) using the passive drool technique under standardized conditions. All samples were obtained in the morning, and participants were instructed to refrain from food and fluid intake for at least 30 minutes prior to collection. Samples were stored at -20°C until analysis.

2.3 Variables and Measurements

2.3.1 Subjective Recovery and Psychological Measures

Subjective recovery-related states were monitored using standardized questionnaires and numerical scales to assess both psychological and physiological dimensions:

- **Psychological States:** Calmness, stress, and anger were assessed using standardized questionnaires, with each variable rated on a 10-point Likert scale.
- **Physiological States:** Self-reported measures included sleep quality, tiredness, muscle soreness, and energy level (each rated on a 1–10 numerical scale), as well as sleep duration (categorized into three levels: less than 5 hours, 5–7 hours, and 7–9 hours).
- **Composite Score:** A comprehensive self-score was calculated by averaging the psychological and physiological questionnaire variables after reverse-coding negatively oriented variables, including stress, anger, tiredness, and muscle soreness, so that higher composite values consistently represented a more favorable psychophysical state.

2.3.2 Biomarkers and Analytical Methods

Six salivary biochemical markers were selected to represent non-invasive, practically accessible indicators across metabolic, muscular, and immune systems in applied athlete-monitoring settings. The specific quantification methods were as follows:

- pH and ketones: quantified using paper-strip dry chemistry (MyFit Strip, USA).
- Immunoglobulin A (IgA): measured using a validated commercial ELISA kit (IgA saliva, DK0078; Diametra, Italy).
- Uric acid, aspartate aminotransferase (AST), and creatine kinase (CK): quantified using an automated clinical chemistry analyzer (BT-3500; Biotechnica Instruments S.p.A., Italy).

2.3.3 Workload and Performance Variables

Table 1 gives performance metrics (n = 25) extracted from official game statistics from LBA Italy. Minutes played during competitive games were used as an indicator of acute competition exposure. Their specific role, including participant selection, adjustment, interaction testing, and group classification, is described within the corresponding statistical analyses. For the performance-profile analysis, players were classified into good and poor performance-readiness groups based on the combined median splits of PIR/min and the self-reported score.

Table 1. Performance metrics extracted from official game statistics from LBA Italy.

Category	Variable	Description
Workload	Minutes Played	Total minutes played by a player during each official LBA Italy game; used as an indicator of acute competition exposure. Players with 0 minutes played were excluded from analyses involving competition exposure.
Scoring	Points	Total points scored per game.
Shooting Performance	2PT Made	Successful two-point field goals.
	2PT Attempted	Attempted two-point field goals.
	2PT %	Two-point field goal percentage.
	3PT Made	Successful three-point field goals.
	3PT Attempted	Attempted three-point field goals.
	3PT %	Three-point field goal percentage.
	FT Made	Successful free throws.
	FT Attempted	Attempted free throws.
	FT %	Free-throw percentage.
Rebounding	Offensive Rebounds	Number of rebounds secured in the offensive phase.
	Defensive Rebounds	Number of rebounds secured in the defensive phase.
	Total Rebounds	Sum of offensive and defensive rebounds.
Ball Handling	Assists	Number of passes leading directly to a scored basket.
	Turnovers	Losses of ball possession.

	Steals	Possessions gained from opponents.
Defensive Actions	Blocks Given	Successful blocked opponent shots.
	Blocks Received	Shots blocked by an opponent.
Fouls	Fouls Committed	Personal fouls committed.
	Fouls Suffered	Personal fouls drawn from opponents.
Efficiency Metrics	Offensive Efficiency Rating (OER)	Measure of offensive productivity and efficiency, calculated as $OER = (Points\ Scored / Possessions) \times 100$.
	Performance Index Rating (PIR)	Composite performance metric provided by LBA Italy to evaluate a player's total statistical contribution in a single game calculated as the sum of a player's positive statistics minus their negative statistics.
	PIR/min	Performance Index Rating normalized to minutes played; used to classify players into performance groups.
	Plus/Minus	Team's point differential recorded while a player is on court.

2.4 Statistical Analysis

Statistical analyses were performed using Python 3.12 software with the following packages: pandas, NumPy, SciPy, statsmodels, and Matplotlib. Statistical significance was set at $p < 0.05$, and Holm's correction was applied to account for multiple comparisons. Given the exploratory nature of the analyses, emphasis was placed on the magnitude and practical relevance of the observed effects in addition to statistical significance.

2.4.1 Descriptive statistics

Descriptive analyses were performed by calculating the mean, standard deviation, and range for quantitative variables (psychophysical states, biomarker profiles, workload variables, and performance metrics), while the categorical variable (sleep time) was summarized using frequencies and percentages.

2.4.2 Correlation analysis

Kendall's rank correlation coefficients (τ) were calculated to examine monotonic associations within and between the biomarker, psychological, and physiological domains. For these analyses, the dataset was filtered to include only observations from recovery days, further restricted to athletes with active game participation (minutes played > 0). Additionally, associations between biomarkers and performance metrics were investigated. Circos plots were used to visualize associations among salivary biomarkers, psychological variables, physiological variables, and cross-domain relationships (Figure 1A–D), with link thickness representing the strength of Kendall's τ correlation. Separately, a heatmap was used to show correlation between salivary biomarkers and performance metrics (Figure 2).

2.4.3 Stratification analysis

Variables of interest were stratified into tertiles (low/medium/high), when possible, and compared across groups using Kruskal–Wallis tests, with results visualized using boxplots (Figure 3, significant findings only).

2.4.4 Risk-enrichment Analysis

A risk-enrichment analysis was performed to examine the association between at-risk psychophysical states and biomarker abnormalities. Trait-positive subgroups were defined using predefined thresholds, representing either high-risk states characterized by elevated scores (e.g., soreness, anger, and tiredness ≥ 7 and ≥ 4) or high-risk states characterized by reduced scores (e.g., calmness and energy ≤ 3). Biomarker abnormalities were assessed using within-sample standardized z-scores and classified as moderate positive deviations ($z \geq 1.0$) or substantial positive deviations ($z \geq 1.5$), whereas negative deviations were defined as $z \leq -1.0$. Risk ratios (RR), risk differences, and odds ratios (OR) were calculated by comparing trait-positive participants with (i) the global event rate and (ii) the trait-negative event rate.

2.4.5 Recovery phenotype analysis

To quantify subjective recovery, delta scores (Δ = recovery score – post-game score) were calculated for each questionnaire-derived variable, with athletes classified as "fast" and "slow recoverers" using a median-split approach. Biomarkers showing the largest differences between recovery phenotypes were compared using Mann–Whitney U tests. Results were presented as boxplots showing medians, interquartile ranges, and individual observations (Figure 4).

2.4.6 Linear mixed model effects

To examine whether associations between subjective recovery changes and biomarkers depended on match exposure (25), linear mixed-effects models were fitted with athletes as a random intercept. Three linear mixed-effects models were fitted for each questionnaire parameter and biomarker combination. Prior to all of the model fitting, recovery biomarker values were standardized as z-scores to facilitate comparison across biomarkers measured on different scales. An unadjusted Δ -only model was first fitted, followed by a model adjusted for minutes played and a model including a Δ score $\times$ minutes played interaction term. In the first two models, the Δ -score coefficient (β) represented the expected change in standardized biomarker concentration associated with a one-unit increase in questionnaire Δ score, before and after adjustment for minutes played, respectively. In the interaction model, the interaction coefficient represented the change in the Δ score–biomarker association with increasing minutes played. Match exposure was additionally categorized as Did Not Play (DNP; 0 min), Low Minutes ($0 < \text{minutes} \leq 23$), or High Minutes (>23 min), and questionnaire Δ scores were compared across the three groups using Kruskal–Wallis tests to determine whether subjective recovery changes differed according to match exposure.

2.4.7 Analysis of variance (ANOVA and MANOVA) / Performance Group Analysis

Finally, to examine differences in psychobiophysical characteristics according to performance profile, observations were classified into "good" and "poor" performance-readiness groups (based on PIR/min and self-score relative to the median). Comparison was made using MANOVA, followed by univariate ANOVAs with Holm correction. The repeated-measures nature of the data (nested within athletes) was accounted for when interpreting the results.

Full details of the statistical procedures, formulas, and classification criteria are reported in Supplementary Material and Methods.

3. Results

3.1 Descriptive characteristics of the dataset

Across 309 observations collected from 13 athletes over the 15-week monitoring period, the longitudinal dataset captured substantial variability in psychophysical states and biomarker profiles. Descriptive statistics for salivary biomarkers, athlete-reported psychological and physiological states, sleep duration, and game-performance variables are presented in Tables 2 and 3. AST and CK showed the greatest inter-observation variability among the salivary biomarkers, while most sleep-duration observations fell within the 5–9 h categories. The 7–9 h category was the most frequent (152 observations; 49.2%), followed by 5–7 h (133 observations; 43.0%), whereas <5 h was reported in 17 observations (5.5%). Sleep-duration data were missing for the remaining 7 observations (2.3%), corresponding to athlete-date observations for which the questionnaire was not completed on that day.

Table 2. Descriptive statistics for biomarker, psychological and physiological variables. Values are presented as mean, standard deviation and observed range.

Biomarker variable	Mean	Standard Deviation	Observed range
Salivary pH	7.17	0.49	6.00 - 8.50
Salivary Uric Acid (mg/dl)	3.91	2.84	0.00 - 13.83
Aspartate aminotransferase (U/L)	29.76	32.99	0.00 - 209.00
Creatine kinase (U/L)	18.93	27.32	0.00 - 270.00
Ketones	1.88	1.87	0.00 - 8.00
Immunoglobulin A (mg/mL)	6.22	2.72	0.90 - 14.67
Calmness	6.78	2.26	1 – 10
Stress Level	3.06	1.75	1 – 9
Anger	2.72	1.78	1 – 9
Sleep quality	6.34	1.49	1 – 9
Tiredness	4.17	1.87	1 – 8
Muscle soreness	3.96	1.86	1 – 9
Energy level	6.12	1.66	1 – 10

Table 3. Descriptive statistics for performance metrics. Values are presented as mean and standard deviation.

Performance metric	Mean	Standard Deviation
--------------------	------	--------------------

Points	7.58	6.64
Minutes played	17.08	11.27
Personal Fouls	1.42	1.34
Personal Fouls Drawn	1.62	1.84
2 Point Field Goals Made	1.38	1.57
2 Point Field Goals Attempted	2.68	2.77
2 Point Field Goals %	35.86	35.57
3 Point Field Goals Made	1.19	1.45
3 Point Field Goals Attempted	3.05	3.12
3 point Field Goals %	25.13	27.68
Free throw made	1.17	1.82
Free throw attempted	1.62	2.23
Free throw %	25.91	39.36
Offensive Rebounds	0.91	1.39
Defensive Rebounds	2.16	2.36
Total Rebounds	3.07	3.16
Blocks	0.14	0.40
Blocks Against	0.17	0.41
Turnovers	1.14	1.46
Steals	0.38	0.68
Assists	1.52	2.14
Offensive Efficiency Rating	0.77	0.57
Plus/minus	-1.32	13.01
PIR	8.13	8.29
PIR/min	0.26	0.41

3.2 Associations and biomarker stratification

3.2.1 Correlation structure among significant variables

Initially, associations exclusively among the six salivary biomarkers were analyzed to establish biochemical interdependencies (Figure 1A). The biomarker-only network showed several positive associations, primarily involving CK, AST, uric acid, and ketones. The strongest association was observed between CK and AST ($\tau = +0.244$). Overall, these findings suggest partial interrelationships among biomarkers associated with metabolic strain, oxidative balance, or tissue-stress responses.

Within the psychological domain (Figure 1B), calmness was inversely associated with stress ($\tau = -0.623$) and anger ($\tau = -0.457$), whereas stress and anger were positively associated with each other ($\tau = +0.522$), indicating a coherent affective profile in which higher negative emotional states clustered together and were opposed to calmness.

Within the physiological domain (Figure 1C), the correlation network suggested meaningful associations among athlete-reported recovery and fatigue measures. The strongest positive associations were observed between sleep-related variables ($\tau = +0.560$) and between tiredness and muscle soreness ($\tau = +0.524$). Better sleep and higher energy were generally associated with lower tiredness and muscle soreness. Overall, these associations support the internal consistency of the physiological self-report measures.

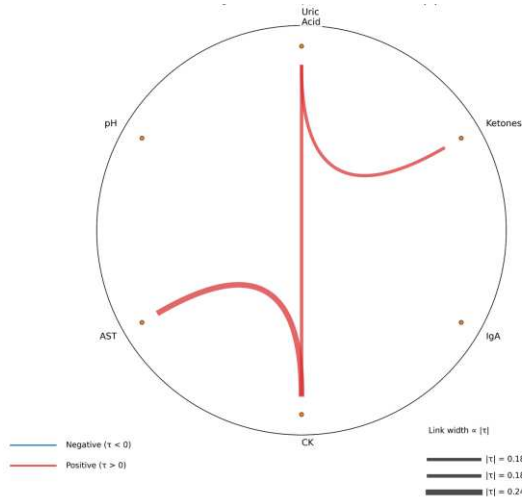
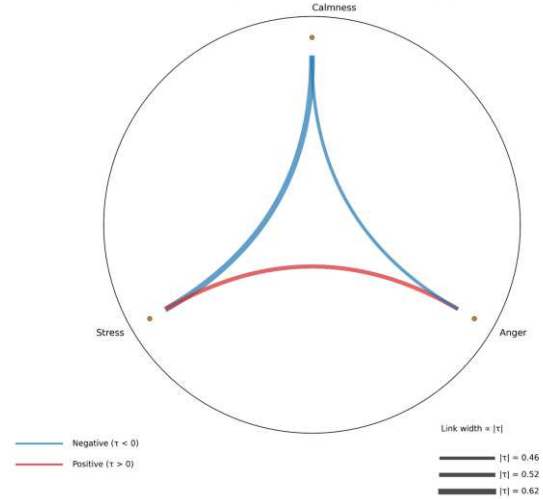
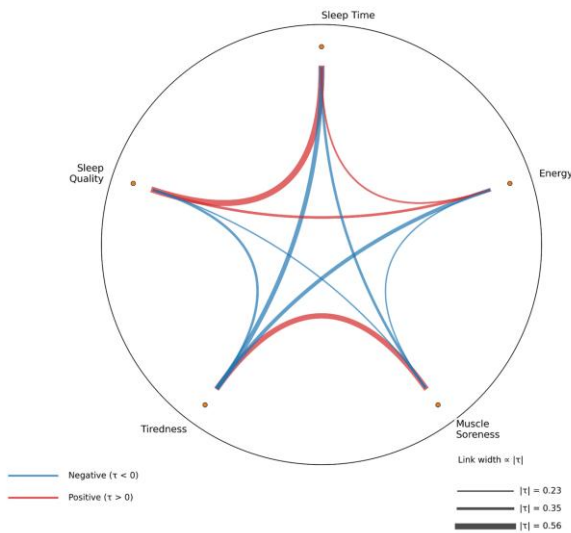
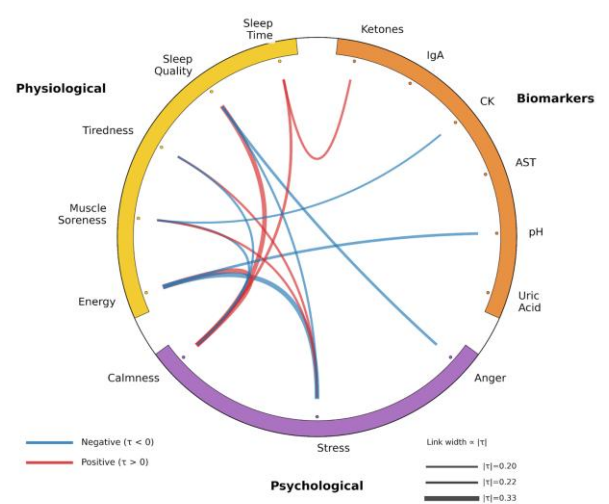
A**B****C****D**

Figure 1. Kendall circos plots of significant correlations. (A)Correlations among salivary biomarker only. (B)Correlation among psychological variables only. (C)Correlation among physiological variables only. (D)Correlation among physiological, psychological and biomarker variables. Only significant associations ($p < 0.05$) are shown. Red links indicate positive correlations, blue links indicate negative correlations, and link width is proportional to the absolute value of the correlation coefficient.

Finally, cross-domain relationships were examined to assess significant associations between biochemical, psychological and physiological variables, although the overall pattern was small-to-moderate in magnitude (Figure 1D). The clearest relationships emerged between psychological and physiological variables: calmness was associated with greater energy and better sleep, whereas stress was associated with lower energy and poorer sleep quality. Tiredness and muscle soreness were also positively associated with stress and inversely

associated with calmness. Significant links were also identified between physiological variables and salivary biomarkers. The strongest relationship was observed between energy and salivary pH ($\tau = -0.246$). No significant associations between psychological variables and biomarkers were identified. Overall, these findings indicate that salivary biomarkers captured only part of the athlete-reported physiological recovery, supporting the use of a multidimensional monitoring approach rather than reliance on a single marker.

3.2.2 Associations between salivary biomarkers and game performance variables

The heatmap analysis (Figure 2) demonstrated several statistically significant but generally weak Kendall correlations between salivary biomarkers and game-derived performance indicators. Salivary pH displayed the most consistent pattern, with positive associations across several indicators of game involvement and offensive performance. Its strongest relationships were observed with three-point field goals made, three-point attempts, and three-point shooting percentage. In contrast, Uric acid, AST, and ketones showed several negative associations with selected shooting, free-throw, turnover, and plus/minus variables. No clear pattern of significant association was observed for CK or IgA. Overall, the magnitude of these associations was modest, suggesting that salivary biomarkers were related to performance primarily as weak state-dependent correlates rather than direct performance predictors.

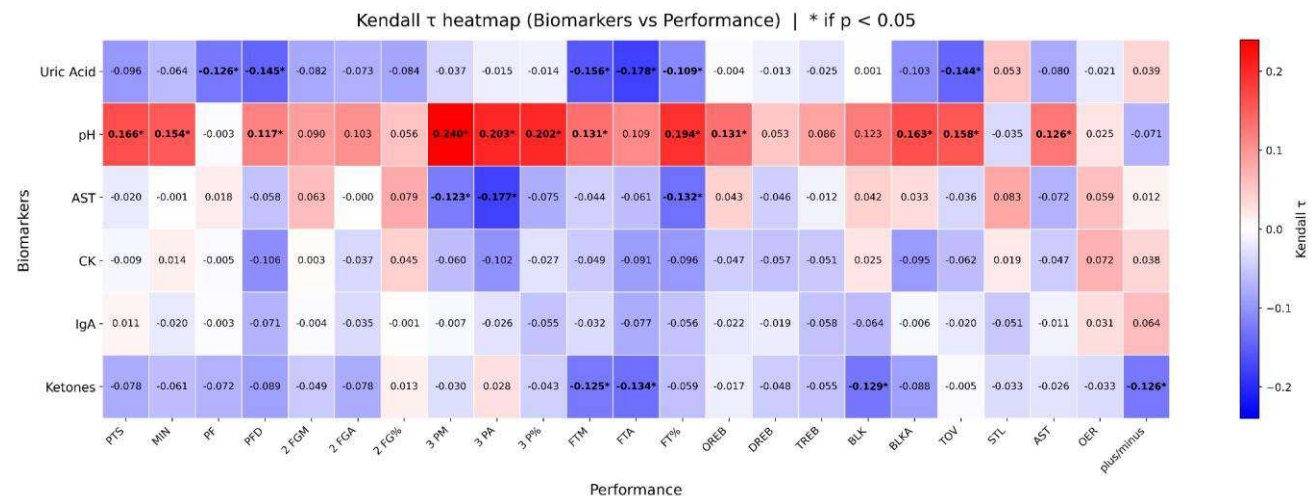
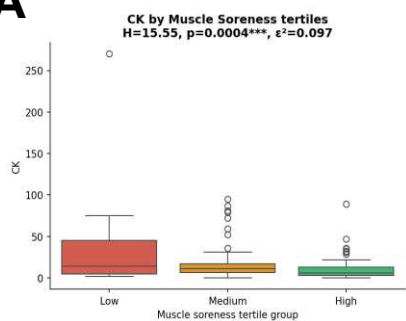
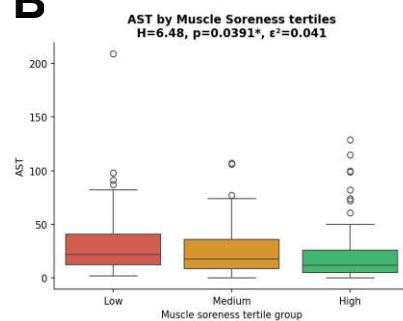
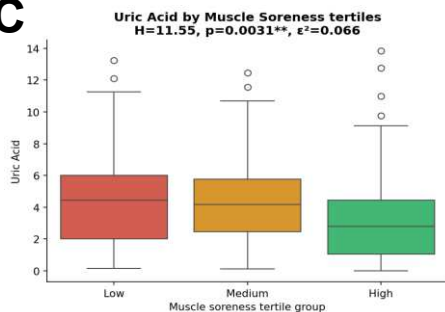
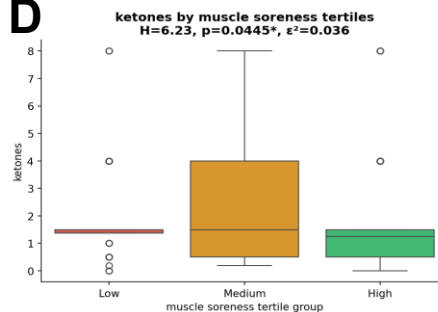


Figure 2. Heat map showing Kendall correlation analysis between performance measures and biomarkers. Statistically significant associations are marked with an asterisk ($p < 0.05$). Negative correlations are shown in blue, and positive correlations in red.

3.2.3 Stratification analyses according to subjective physiological and psychological states

Stratification analyses in Figure 3(A-I) further indicated that biomarker distributions differed across athlete-reported recovery and affective states. Muscle-soreness tertiles (Figure 3A-D), CK, AST, Uric acid, and Ketones differed significantly between groups. Effect sizes were generally small to moderate, and the distributions were not consistently linear across increasing levels of the athlete-reported variables. Additional stratification analyses showed that AST differed according to energy-level tertiles and stress tertiles (Figure E-F). In figures 3G-I, Salivary pH also differed according to energy level, tiredness, and anger. Overall, the stratification analyses identified biomarker-specific differences across selected athlete-reported physiological and affective states.

A**B****C****D**

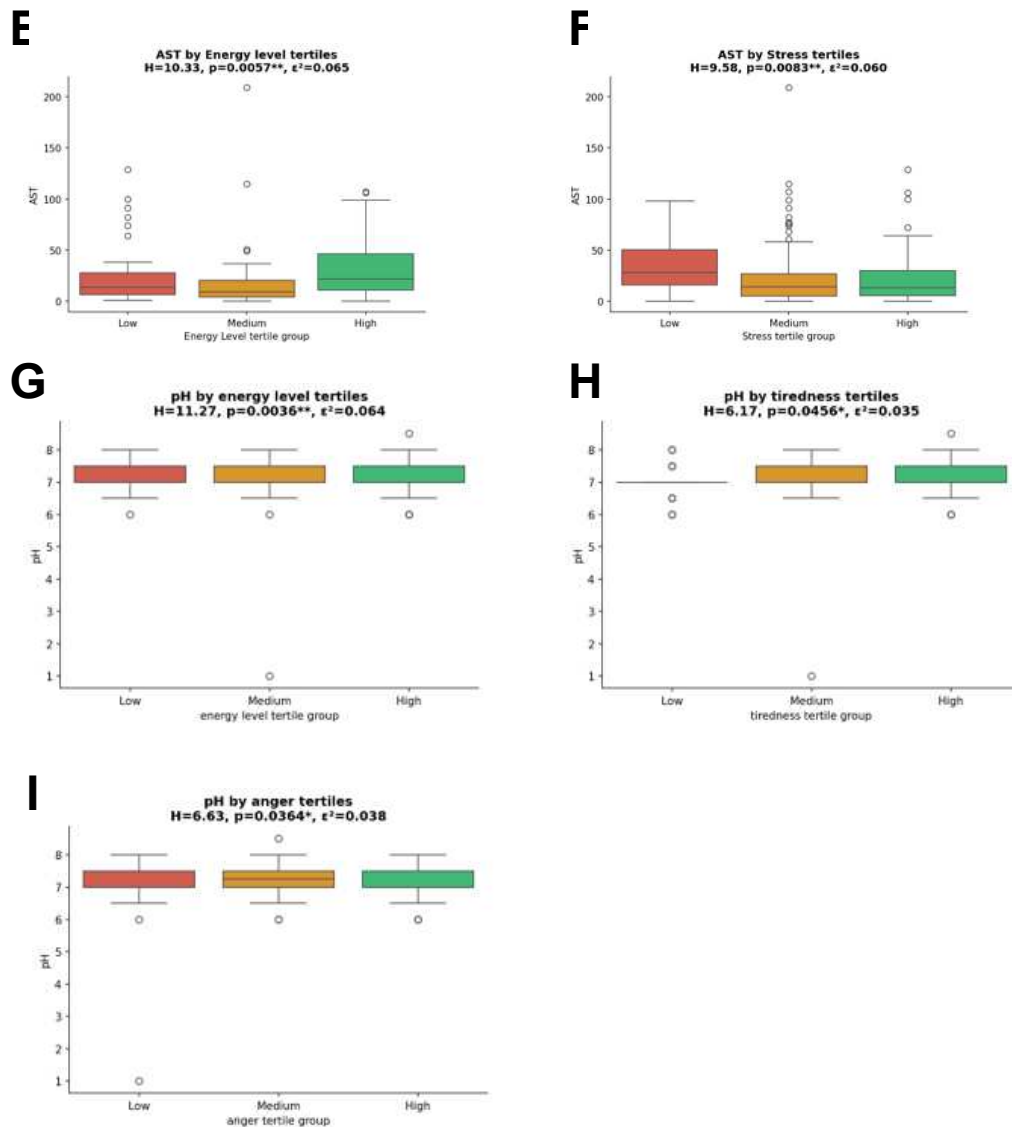


Figure 3. Tertile stratification of muscle soreness, energy, tiredness, anger, and stress.

3.3 Risk enrichment within High-Risk athlete-reported states

Risk-enrichment analysis identified several combinations of subjective traits and biomarker abnormalities associated with elevated relative risk compared with trait-negative observations (Table 4). Severe muscle soreness (≥ 7) was strongly enriched for low IgA, high AST, and both high and low ketones, with risk ratios relative to trait-negative observations ranging from 4.31 to 5.05. Low energy (≤ 3) was associated with enrichment for high IgA and low ketones, while high anger (≥ 7) was enriched for high IgA. Moderate-to-high soreness (≥ 4) was also associated with enrichment for low uric acid. These findings suggest that extreme self-reported states may identify subgroups with disproportionate biomarker abnormalities, particularly involving IgA, ketones, AST, and uric acid.

Table 4. Exploratory enrichment of biomarker abnormalities across psychophysical trait thresholds. Trait-positive subgroups were defined using prespecified psychophysical cutoffs, corresponding to moderate (≥ 4) or high/severe (≥ 7) elevated states for traits in which higher scores indicate a less favorable psychophysical status, and high-risk reduced states (≤ 3) for traits in which lower scores indicate a less favorable psychophysical status. Biomarker abnormalities were defined using within-sample z-score thresholds, with negative deviations defined as $z \leq -1.0$, moderate positive deviations as $z \geq 1.0$, and substantial positive deviations as $z \geq 1.5$. Values represent event rates in the trait-positive and trait-negative subgroups, together with the corresponding risk ratios (RR) and odds ratios (OR).

Trait threshold	Biomarker abnormality	Trait positive rate	Trait negative rate (RR)	Global (RR)	OR
Soreness ≥ 7	IgA $z \leq -1.0$	75.0%	14.9% (5.05)	16.4% (4.56)	13.12
Soreness ≥ 7	Ketones $z \geq 1.5$	17.6%	3.7% (4.74)	4.7% (3.72)	5.89
Soreness ≥ 7	Ketones $z \leq -1.0$	17.6%	3.7% (4.74)	4.7% (3.72)	5.89
Soreness ≥ 7	AST $z \geq 1.5$	27.3%	6.3% (4.31)	7.6% (3.60)	5.85
Energy ≤ 3	IgA $z \geq 1.5$	33.3%	9.4% (3.55)	9.9% (3.38)	5.61
Energy ≤ 3	Ketones $z \leq -1.0$	14.3%	4.1% (3.46)	4.7% (3.01)	4.41
Anger ≥ 7	IgA $z \geq 1.0$	50.0%	15.1% (3.32)	16.4% (3.04)	5.53
Soreness ≥ 4	Uric acid $z \leq -1.0$	23.5%	7.1% (3.32)	15.5% (1.52)	3.87

3.4 Biomarkers differentiating Fast and Slow subjective recovery Phenotypes

Fast and slow recovery phenotypes, derived from post-game to recovery change scores, were differentiated by selected salivary biomarkers. Figure 4 (A-D) shows the significant Mann-Whitney U test results comparing recovery salivary biomarkers between fast and slow recovery groups. Median-split comparisons suggested that different biomarkers were associated with different subjective recovery dimensions. For tiredness recovery, salivary pH differed significantly between fast and slow recoverers ($p = 0.0167$), with the visual distribution suggesting higher pH values among faster recoverers. For energy recovery, AST differed between groups ($p = 0.0130$), with slow recoverers showing a higher and more dispersed AST distribution. AST also differentiated fast and slow recovery profiles for calmness ($p = 0.0240$) and anger ($p = 0.0385$). These findings indicate that AST may be particularly informative for distinguishing slower recovery in psychological-energy dimensions, specifically energy, calmness, and anger, whereas salivary pH may be more closely linked to perceived tiredness recovery.

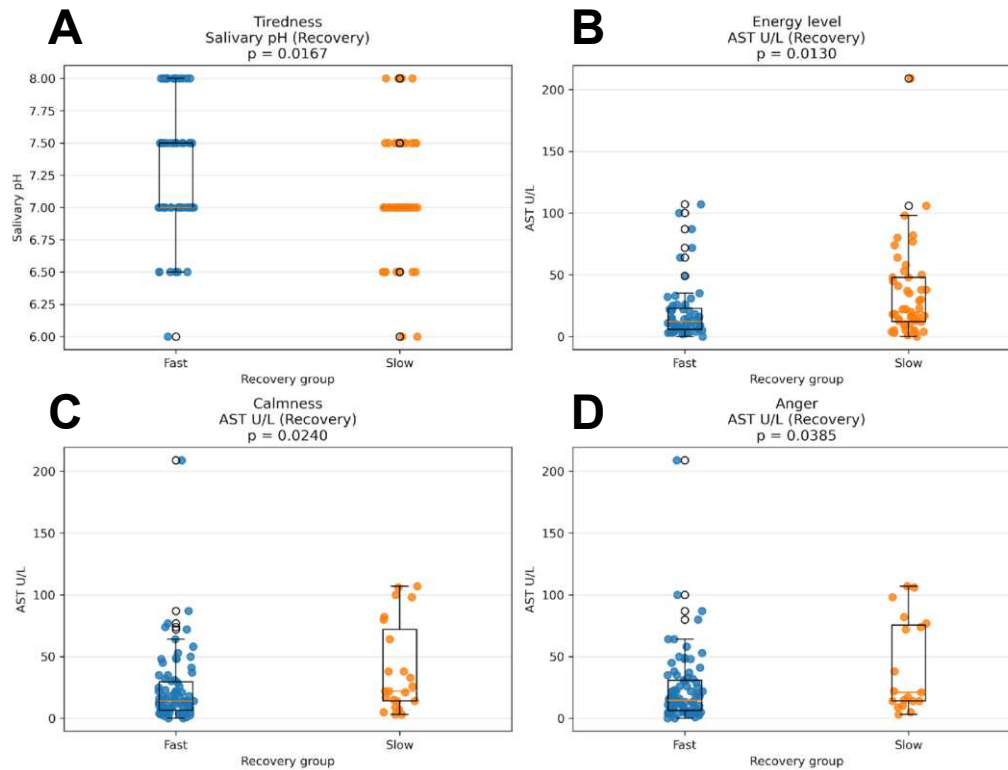


Figure 4. Recovery biomarkers differentiating fast and slow recovery phenotypes across questionnaire parameters. For each questionnaire parameter, the recovery biomarker showing the strongest difference between fast and slow recoverers is displayed. Fast and slow phenotypes were derived from post-game to recovery change scores. Boxplots show median and interquartile range, with individual observations overlaid. P-values are from two-sided Mann–Whitney U tests.

3.5 Subjective Change Scores, Minutes Played, and Biomarkers

To further investigate the relationships between Δ scores (recovery minus post-game) and salivary biomarkers, linear mixed-effects models were performed. These models were first tested using Δ scores alone, then adjusted for minutes played and finally included a $\Delta \times$ minutes interaction term to assess whether the association varied according to match exposure (Table 5). For tiredness, the negative association with salivary pH was borderline in the Δ -only model and became statistically significant after adjustment for minutes played. No significant $\Delta \times$ minutes interaction was found for pH. In contrast, significant interactions with minutes played were identified for tiredness in relation to AST and uric acid. For calmness, a significant negative association with ketones was observed in the Δ -only model, although this became borderline after adjustment for minutes played. Significant $\Delta \times$ minutes interactions were found for ketones and AST. $\Delta \times$ anger showed significant positive associations with ketones and CK in the Δ -only models. These relationships remained significant after adjustment for minutes played for both ketones and CK. No significant $\Delta \times$ minutes interaction was detected for ketones while the interaction for CK approached significance, indicating that the relationships were largely independent of playing time. Regarding energy levels, no significant associations were identified in the Δ -only models. After adjustment for minutes played, borderline negative link was observed with AST and ketones.

Finally, questionnaire Δ scores did not differ significantly across minutes-played groups for tiredness, calmness, anger, or energy level (Table 5). This suggests that the degree of subjective change from post-game

to recovery was not significantly different between athletes classified as DidNotPlayed, LowMinutes, and HighMinutes.

Overall, the clearest adjusted associations involved tiredness Δ with salivary pH and anger Δ with ketones and CK, whereas selected associations involving tiredness and calmness varied according to minutes played. Questionnaire Δ scores did not differ significantly across the did-not-play, low-minutes, and high-minutes groups.

Table 5. Associations between questionnaire delta scores and recovery biomarkers after accounting for minutes played. Δ was calculated as recovery minus post-game. Results are shown for Δ only linear mixed-effects models, models adjusted for minutes played and models including a $\Delta \times$ minutes interaction term. The final column reports the p-value for differences in Δ score across minutes-played groups (did not play, low minutes, high minutes).

Parameter	Biomarker	Δ only, β (p)	Adjusted for minutes, β (p)	$\Delta \times$ minutes, β (p)	Δ across minutes groups, p
Tiredness	pH	-0.101 (0.057)	-0.110 (0.046)	0.001 (0.780)	0.164
Tiredness	AST	-0.044 (0.440)	-0.032 (0.586)	0.013 (0.009)	0.164
Tiredness	Uric acid	-0.015 (0.778)	-0.003 (0.954)	0.009 (0.035)	0.164
Calmness	Ketones	-0.105 (0.035)	-0.101 (0.057)	0.015 (0.013)	0.208
Calmness	AST	-0.088 (0.081)	-0.094 (0.063)	0.012 (0.027)	0.208
Anger	Ketones	0.174 (0.011)	0.171 (0.010)	-0.008 (0.272)	0.768
Anger	CK	0.162 (0.024)	0.166 (0.020)	-0.016 (0.057)	0.768
Energy level	AST	-0.101 (0.131)	-0.129 (0.056)	-0.006 (0.408)	0.534
Energy level	Ketones	-0.103 (0.136)	-0.117 (0.097)	0.005 (0.507)	0.534

3.6 Performance-readiness Profiles

Good- and poor-performance groups showed clearly differentiated psychobiophysical profiles (Figure 5). The MANOVA performed on psychobiosocial direction scores demonstrated a significant multivariate group effect, Wilks' $\lambda = 0.3564$, $F(7, 97) = 25.0187$, $p < 0.001$, with a corresponding Pillai's trace of 0.6436. In the raw-score profile, the good-performance group reported higher sleep quality (7.19 ± 1.09 vs. 5.58 ± 1.51), higher energy level (7.06 ± 1.31 vs. 5.32 ± 1.66), and greater calmness (8.27 ± 1.86 vs. 5.17 ± 2.04) compared with the poor-performance group. Conversely, the good-performance group reported lower tiredness (3.19 ± 1.44 vs. 4.57 ± 2.00), stress (1.98 ± 1.09 vs. 4.26 ± 1.91), anger (1.98 ± 1.20 vs. 3.64 ± 2.16), and muscle soreness (2.96 ± 1.40 vs. 4.64 ± 2.04).

Follow-up univariate ANOVAs indicated that good performances-readiness observations were characterized by greater calmness, lower stress level, better sleep quality, higher energy level, and less muscle soreness. Among biomarkers, only salivary IgA also differed significantly between performance groups. The poor-performance-readiness observations showed higher IgA concentrations than the good-performance group (7.55 vs. 5.57 mg/mL), with the ANOVA indicating a statistically significant group effect, $F = 8.9367$, uncorrected $p = 0.0043$, Holm-corrected $p = 0.0341$. Thus, although better performance was associated with a more favorable subjective recovery and psychological profile, it was accompanied by lower salivary IgA concentrations compared with poor-performance observations.

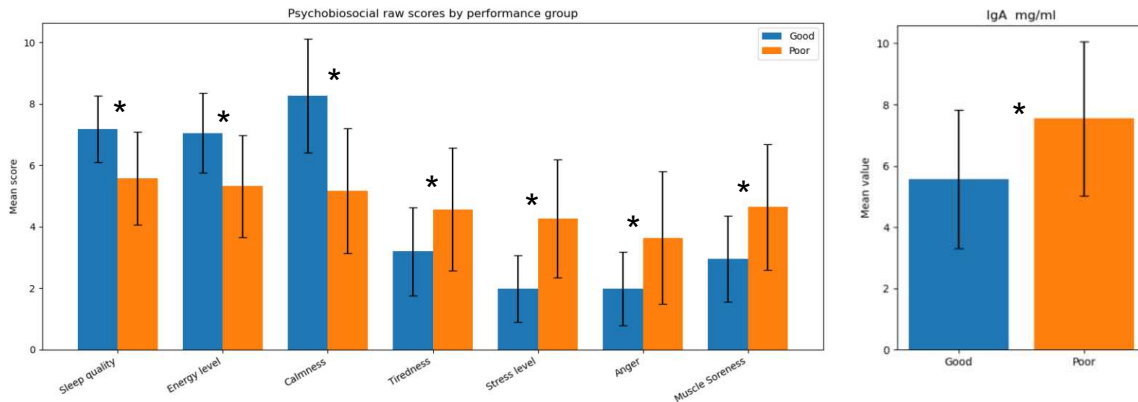


Figure 5. Mean ($\pm$ SD) salivary IgA concentration in the good and poor performance groups.

4. Discussion

This exploratory longitudinal field study examined the relationships among salivary biomarkers, athlete-reported psychological and physiological states, recovery phenotypes, and basketball performance indicators across a competitive season. The main findings were that: (i) athlete-reported psychological and physiological variables showed coherent within-domain recovery-fatigue patterns, while salivary biomarkers exhibited significant but generally modest associations with athlete-reported states and game-performance variables; biomarker distributions also differed across selected levels of soreness, energy, stress, tiredness, and anger; (ii) severe soreness, low energy, and high anger were enriched for specific biomarker abnormalities, particularly involving IgA, ketones, AST, and uric acid; (iii) salivary pH and AST differentiated fast and slow subjective recovery phenotypes across different recovery dimensions; (iv) selected associations between subjective recovery changes and biomarkers remained significant after adjustment for minutes played, whereas others varied according to competition exposure; and (v) good-performance-readiness observations showed a more favorable athlete-reported psychobiophysical profile, whereas poor-performance-readiness observations showed higher salivary IgA concentrations..

Overall, these results support a multidimensional approach to athlete monitoring. Contemporary athlete-monitoring frameworks emphasize that no single marker provides a definitive index of fatigue, readiness, or adaptation; in this line, training and competition responses should be interpreted through the integration of internal load, external load, self-report measures, performance indicators, and biological markers (4). The present findings are consistent with this multidimensional monitoring framework (4), as salivary markers did not uniformly explain athlete-reported measures. This is also consistent with evidence showing that athlete-reported measures are sensitive to acute and chronic changes in athlete well-being and may be practical tools for routine monitoring when integrated into broader athlete-management systems (9).

The association analyses showed coherent patterns within the athlete-reported psychological and physiological domains, but only limited cross-domain relationships with salivary biomarkers. The absence of strong direct correlations between psychological variables and biomarkers reinforces the need to avoid simplistic psychophysiological interpretation. Biomarker associations with performance variables were also generally weak. Salivary pH showed the most consistent positive relationships with shooting and game-involvement indicators, whereas uric acid showed predominantly negative relationships with selected performance variables. These associations may reflect shared exposure, redox balance, antioxidant responses, or metabolic strain rather than direct effects on basketball performance. Accordingly, the biomarkers appeared to provide contextual information rather than act as direct performance predictors (26,27).

The stratification analyses further showed that selected biomarker distributions differed across athlete-reported recovery and affective states. Soreness tertiles differed significantly for CK, AST, uric acid, and ketones; energy and stress tertiles differed for AST; and salivary pH differed across levels of energy, tiredness, and anger. However, these patterns were biomarker-specific and were not consistently linear. In particular, observations in the highest soreness tertile did not show the highest CK concentrations, differing from the pattern that might be expected if perceived soreness directly reflected enzymatic evidence of muscle damage. This finding may be explained by the different time courses of perceived muscle soreness and CK responses, as peak CK concentrations and peak soreness do not necessarily occur at the same time after exercise (28).

The risk-enrichment analyses extended these findings by showing that selected adverse athlete-reported states may function as practical screening flags for disproportionate biomarker abnormalities.

Muscle soreness emerged as one of the most informative athlete-reported signals. Severe soreness was enriched for low IgA, high AST and both unusually high and unusually low ketones, while moderate-to-high soreness was associated with low uric acid. The bidirectional ketone finding suggests greater metabolic heterogeneity rather than a uniform increase or decrease in ketone concentrations. CK and AST are commonly interpreted as indirect markers of exercise-induced muscle damage or tissue stress, but their responses are influenced by exercise type, timing of sampling, muscle mass, training status, previous exposure to similar loads, individual responder phenotype, and clearance kinetics (29). In basketball, soreness may arise from eccentric loading, repeated jumping and landing, rapid decelerations, contacts, and localized muscle damage. Overall, severe subjective soreness may help identify observations with a greater frequency of selected immune, enzymatic, and metabolic biomarker abnormalities, particularly involving IgA, AST, and ketones. Moderate-to-high soreness was also associated with low uric acid. However, these responses were heterogeneous and non-linear, and both their direction and magnitude varied across biomarkers.

Low energy also emerged as an important monitoring signal. Observations with low energy were enriched for high IgA and low ketones, suggesting that reduced perceived vitality may coincide with immune or metabolic deviations. The association with IgA may indicate immune activation, accumulated strain, or salivary concentration effects, whereas the association with low ketones should be interpreted cautiously because ketone values are influenced by recent dietary intake, fasting duration, carbohydrate availability, and assay characteristics. Thus, low energy should not be treated as a specific marker of metabolic insufficiency. Instead, it may serve as a practical screening item indicating that the athlete's recovery status requires closer contextual evaluation, particularly when low energy coincides with biomarker deviations, poor sleep, high soreness, or heavy recent match exposure. This interpretation is consistent with the literature on under-recovery and energy availability. Some negative outcomes attributed to training overload may be related to under-fueling, Relative Energy Deficiency in Sport (RED-S) or low carbohydrate availability(30). Under-fueling can lead to a "maladapted state" characterized by hormonal perturbations and persistent fatigue (30,31). Therefore, the association between low energy and biomarker abnormalities in the present study should not be interpreted as evidence of a single metabolic mechanism, but rather as support for the use of athlete-reported energy ratings as a low-burden screening tool within a multidimensional athlete-monitoring framework (10).

Anger provided additional information about the psychological dimension of recovery. High anger was enriched for high IgA, suggesting that marked negative affect may coincide with selected immune alterations. However, this pattern was less consistent than that observed for soreness and should not be interpreted as evidence of a

direct psychobiological mechanism. Anger may reflect psychological stress, competitive frustration, poor recovery, external life stressors, or an individual emotional response to underperformance. Together, the enrichment findings suggest that soreness, low energy, and high anger may help identify observations requiring closer evaluation, but these states should be treated as broad screening signals rather than specific indicators of a single underlying physiological process.

Fast and slow subjective recovery phenotypes were also differentiated by selected salivary biomarkers. Salivary pH differentiated fast and slow tiredness recovery, whereas AST differentiated recovery in energy, calmness and anger. Salivary pH may reflect hydration status, oral buffering capacity, diet, salivary flow, or physiological stress, while AST is an indirect tissue-stress marker with substantial biological variability. These findings therefore suggest that pH and AST may provide complementary information about different dimensions of subjective recovery. However, their usefulness is more likely to lie in contextual longitudinal monitoring than in the isolated interpretation of absolute values.

The mixed-effects findings further showed that biomarker–recovery relationships depended on both the dimension of change in athlete-reported states and competition exposure, represented by minutes played. After adjustment for minutes played, changes in tiredness were associated with salivary pH, while changes in anger remained positively associated with ketones and CK. Changes in energy showed borderline negative associations with AST and ketones after adjustment for minutes played. In addition, significant interactions with minutes played were observed for tiredness in relation to AST and uric acid and for calmness in relation to ketones and AST. The absence of a significant tiredness x minutes interaction for pH suggests that this association was not primarily explained by playing time. Overall, these results indicate that the same subjective recovery change may have different biochemical correlates depending on recent match involvement. Minutes played is an imperfect workload metric because it does not capture accelerations, decelerations, contacts, positional role, tactical responsibility, internal load, or travel-related fatigue; therefore, it should be interpreted as only a partial indicator of competition exposure rather than a complete workload measure (7,32,33). Nevertheless, minutes played remains a practical index of acute match involvement. These findings support a central practical conclusion: biomarker dashboards should not classify values as simply “normal” or “abnormal” without considering recent playing time, role demands, sport-specific context, and individual baseline history(34).

The performance-group findings provide a useful but preliminary link between monitoring variables and competitive output. Good-performance observations were characterized by a favorable subjective profile, including better sleep quality, higher energy and calmness, and lower tiredness, stress, anger, and soreness. The role of sleep is particularly relevant, as sleep loss has been associated with impaired sport-specific performance, altered physiological responses, immune dysfunction, and slower or less accurate cognitive performance in athletes (35). In basketball, where repeated high-intensity efforts, decision-making, emotional regulation, and technical execution interact, the combination of high energy and calmness with low stress and soreness may reflect a favorable readiness state for game performance. The IgA results require careful interpretation because they appear directionally complex. Poor-performance observations showed higher IgA than good-performance observations, whereas severe soreness was enriched for low IgA. Rather than representing a contradiction, these findings may reflect different biological contexts and the substantial intra- and inter-individual variability of salivary IgA. Salivary IgA is a first-line mucosal immune marker and previous evidence in team sports has linked salivary IgA with training load management and upper respiratory tract infection risk (10,23). In elite athletes, reductions in salivary IgA have also been observed before upper respiratory infection episodes, although absolute IgA concentration shows considerable variability (36). At the same time, systematic-review evidence indicates heterogeneous findings and very low certainty of evidence regarding changes in salivary IgA concentration after exercise (37). In this context, low IgA in severely muscle sore observations may indicate reduced mucosal immune protection during periods of high strain, whereas higher IgA in poor-performance observations may reflect a different acute context, such as immune activation, altered salivary concentration, recent illness exposure, or oral health status, or individualized responses to cumulative stress. The performance-group findings should nevertheless be interpreted cautiously because classification was based

on both PIR/min and self-score. Although this approach increases the contrast between groups, it also raises a potential circularity concern because the subjective state partly contributes to group allocation. These results should be presented as descriptive psychobiophysical profiling rather than as evidence that the measured variables independently predict performance. Future models should test performance outcomes using approaches that account for repeated observations within athletes and avoid embedding subjective state in the performance-group definition.

Taken together, the present findings have several practical implications. First, the generally modest associations across athlete-reported states, salivary biomarkers, and performance variables indicate that salivary biomarkers should be interpreted as components of a multidimensional profile rather than as independent diagnostic markers (4,7). Second, high soreness and low energy may be useful low-burden screening flags in elite basketball monitoring, particularly when they coincide with deviations in IgA, AST, ketones, or uric acid. Third, the differentiation of fast and slow subjective recovery phenotypes by salivary pH and AST suggests that selected biomarkers may provide complementary information about recovery dynamics when interpreted longitudinally. Fourth, minutes played and recent match context should be incorporated into biomarker interpretation, because minutes played modifies associations between subjective change and biochemical state. Fifth, integrated subjective, biochemical, and performance-readiness profiles may support contextual evaluation of athlete status, although athlete-specific longitudinal baselines are likely to be more informative than universal cutoffs, especially for markers such as CK, AST, IgA, pH, uric acid, and ketones, which show substantial biological and methodological variability (34). Finally, due to the exploratory nature of the study, monitoring outputs should be used to guide discussion, follow-up assessment, and recovery planning rather than to make deterministic decisions about athlete readiness.

5. Limitations and Future Directions

This study was limited by the inclusion of a single elite male basketball team ($n = 13$), which restricts generalizability and athlete-level statistical inference. Although 309 observations were collected, repeated measurements were nested within athletes, and findings from exploratory observation-level analyses should be interpreted with caution. Biomarker abnormality thresholds were derived from within-sample z-scores rather than validated clinical or individualized cutoffs and therefore reflect relative deviations rather than diagnostic abnormalities. Furthermore, salivary biomarkers are influenced by factors such as collection timing, hydration status, oral health, dietary intake, illness, and salivary flow rate.

Subjective psychophysical status was assessed using a questionnaire adapted from the Profile of Mood States (POMS) (38). Specifically, only selected variables considered relevant to the monitoring protocol (calmness, anger, tiredness, and energy) were retained, while additional items assessing muscle soreness and sleep quality were included. As this modified version does not correspond to the original validated POMS and has not undergone formal psychometric validation (e.g., reliability and construct validity) in this population, its use represents a methodological limitation. This may reduce the comparability of the present findings with studies employing the complete and validated POMS or other standardized athlete-monitoring instruments.

Additional limitations include the use of median-based dichotomization for the performance-readiness classification, the inclusion of the subjective composite score in group definition, the reliance on minutes played as an incomplete proxy for competition exposure, and the observational design, which precludes causal inference.

Future studies should replicate these findings in larger, multi-team cohorts using longitudinal mixed-effects approaches and individualized monitoring thresholds. Incorporating detailed external- and internal-load metrics, salivary flow and secretion rates, nutritional and hydration data, and objective performance measures may improve interpretation of biomarker responses. Intervention studies are also warranted to determine whether monitoring-informed recovery and workload-management strategies enhance athlete recovery and performance.

6. Conclusion

This exploratory 15-week field study suggests that selected athlete-reported recovery states align with salivary and biochemical marker patterns in elite basketball players. High soreness, low energy were the clearest subjective flags of biomarker abnormality, while salivary pH and AST differentiated distinct fast and slow subjective recovery phenotypes. Mixed-effects models further showed that selected associations between changes in athlete-reported states and salivary biomarkers remained after adjustment for minutes played, whereas others varied according to competition exposure. Good- and poor-performance-readiness observations also showed different integrated psychobiophysical profiles, although these findings should be interpreted descriptively. Overall, these findings support multidimensional athlete monitoring but do not justify diagnostic biomarker cutoffs or causal claims. For applied use and future research, the most defensible approach is to interpret subjective states, biomarkers, and workload together, longitudinally, and relative to individual athlete baselines.

Declarations

CONFLICT OF INTEREST

The authors declare no conflict of interest.

FUNDING

The study is supported by the Booster Grant for Life Sciences of the Regione Autonoma Friuli Venezia Giulia (CUP: G97H24001640002).

ACKNOWLEDGMENTS

All authors acknowledge that the results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation, and state that results of the present study do not constitute endorsement by ACSM.

We thank Giulia Cordaro at CRI for her technical support and Paolo Soave for his administrative assistance at CRI.

References

1. Burger J, Henze AS, Voit T, Latzel R, Moser O. Athlete Monitoring Systems in Elite Men's Basketball: Challenges, Recommendations, and Future Perspectives. Mendias C, editor. *Transl Sports Med.* 2024 Jan 18;2024(1). doi:10.1155/2024/6326566
2. Stojanović E, Stojiljković N, Scanlan AT, Dalbo VJ, Berkelmans DM, Milanović Z. The Activity Demands and Physiological Responses Encountered During Basketball Match-Play: A Systematic Review. *Sports Medicine.* 2018 Jan 16;48(1):111–35. doi:10.1007/s40279-017-0794-z
3. Ben Abdelkrim N, Castagna C, Jabri I, Battikh T, El Fazaa S, Ati J El. Activity Profile and Physiological Requirements of Junior Elite Basketball Players in Relation to Aerobic-Anaerobic Fitness. *J Strength Cond Res.* 2010 Sep;24(9):2330–42. doi:10.1519/JSC.0b013e3181e381c1

4. Halson SL. Monitoring Training Load to Understand Fatigue in Athletes. *Sports Medicine*. Springer International Publishing; 2014. p. 139–47. doi:10.1007/s40279-014-0253-z PubMed PMID: 25200666.
5. Kellmann M, Bertollo M, Bosquet L, Brink M, Coutts AJ, Duffield R, et al. Recovery and Performance in Sport: Consensus Statement. *Int J Sports Physiol Perform*. 2018 Feb;13(2):240–5. doi:10.1123/ijsp.2017-0759
6. Meeusen R, Duclos M, Foster C, Fry A, Gleeson M, Nieman D, et al. Prevention, diagnosis and treatment of the overtraining syndrome: Joint consensus statement of the European College of Sport Science (ECSS) and the American College of Sports Medicine (ACSM). *Eur J Sport Sci*. 2013 Jan 16;13(1):1–24. doi:10.1080/17461391.2012.730061
7. Bourdon PC, Cardinale M, Murray A, Gatin P, Kellmann M, Varley MC, et al. Monitoring athlete training loads: Consensus statement. *Int J Sports Physiol Perform*. 2017 Apr 1;12:161–70. doi:10.1123/IJSP.2017-0208 PubMed PMID: 28463642.
8. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and External Training Load: 15 Years On. *Int J Sports Physiol Perform*. 2019 Feb;14(2):270–3. doi:10.1123/ijsp.2018-0935
9. Saw AE, Main LC, Gatin PB. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. *British Journal of Sports Medicine*. BMJ Publishing Group; 2016. p. 281–91. doi:10.1136/bjsports-2015-094758 PubMed PMID: 26423706.
10. Lee EC, Fragala MS, Kavouras SA, Queen RM, Pryor JL, Casa DJ. Biomarkers in Sports and Exercise: Tracking Health, Performance, and Recovery in Athletes. *J Strength Cond Res*. 2017 Oct;31(10):2920–37. doi:10.1519/JSC.0000000000002122
11. Pedlar CR, Newell J, Lewis NA. Blood Biomarker Profiling and Monitoring for High-Performance Physiology and Nutrition: Current Perspectives, Limitations and Recommendations. *Sports Medicine*. 2019 Dec 6;49(S2):185–98. doi:10.1007/s40279-019-01158-x
12. Papacosta E, Nassis GP. Saliva as a tool for monitoring steroid, peptide and immune markers in sport and exercise science. *J Sci Med Sport*. 2011 Sep;14(5):424–34. doi:10.1016/j.jsams.2011.03.004
13. Humphrey SP, Williamson RT. A review of saliva: Normal composition, flow, and function. *J Prosthet Dent*. 2001 Feb;85(2):162–9. doi:10.1067/mp.2001.113778
14. Chicharro JL, Lucía A, Pérez M, Vaquero AF, Ureña R. Saliva Composition and Exercise. *Sports Medicine*. 1998 Jul 23;26(1):17–27. doi:10.2165/00007256-199826010-00002
15. Brancaccio M, Patton AP, Chesham JE, Maywood ES, Hastings MH. Astrocytes Control Circadian Timekeeping in the Suprachiasmatic Nucleus via Glutamatergic Signaling. *Neuron*. 2017 Mar;93(6):1420-1435.e5. doi:10.1016/j.neuron.2017.02.030
16. Brancaccio P, Limongelli FM, Maffulli N. Monitoring of serum enzymes in sport. *Br J Sports Med*. 2006 Feb;40(2):96–7. doi:10.1136/bjsm.2005.020719
17. González Fernández Á, de la Rubia Ortí JE, Franco-Martínez L, Ceron JJ, Mariscal G, Barrios C. Changes in Salivary Levels of Creatine Kinase, Lactate Dehydrogenase, and Aspartate Aminotransferase after Playing Rugby Sevens: The Influence of Gender. *Int J Environ Res Public Health*. 2020 Nov 5;17(21):8165. doi:10.3390/ijerph17218165
18. Fernández-Verdejo R, Mey JT, Ravussin E. Effects of ketone bodies on energy expenditure, substrate utilization, and energy intake in humans. *J Lipid Res*. 2023 Oct;64(10):100442. doi:10.1016/j.jlr.2023.100442

19. Tabatabaei Dakhili SA, Yang K, Stenlund MJ, Ussher JR. The multifaceted roles of ketones in physiology. *Exp Physiol*. 2026 Jan 11;111(1):1–13. doi:10.1113/EP092243
20. Li Y, Liu Q, Jia Z, Guo B. Ketone bodies in exercise, health and disease: Metabolic mechanisms, pathophysiology, and therapeutic implications. *Advanced Exercise and Health Science*. 2025 Jun;2(2):83–93. doi:10.1016/j.aehs.2025.05.004
21. Gleeson PJ, Camara NOS, Launay P, Lehuen A, Monteiro RC. Immunoglobulin A Antibodies: From Protection to Harmful Roles. *Immunol Rev*. 2024 Nov 23;328(1):171–91. doi:10.1111/imr.13424
22. Mantis NJ, Rol N, Corthésy B. Secretory IgA's complex roles in immunity and mucosal homeostasis in the gut. *Mucosal Immunol*. 2011 Nov;4(6):603–11. doi:10.1038/mi.2011.41
23. Rico-González M, Clemente FM, Oliveira R, Bustamante-Hernández N, Pino-Ortega J. Part I: Relationship among Training Load Management, Salivary Immunoglobulin A, and Upper Respiratory Tract Infection in Team Sport: A Systematic Review. *Healthcare*. 2021 Mar 24;9(4):366. doi:10.3390/healthcare9040366
24. Corazza G, Jamil S, Dema R, Zorba S, Bonetta L, Cavalliero D, et al. A Case Study using Physiological and Wellness Indicators for Performance Optimization in Basketball. 2026. doi:10.21203/rs.3.rs-8815351/v1
25. Newans T, Bellinger P, Drovandi C, Buxton S, Minahan C. The Utility of Mixed Models in Sport Science: A Call for Further Adoption in Longitudinal Data Sets. *Int J Sports Physiol Perform*. 2022 Aug 1;17(8):1289–95. doi:10.1123/ijsp.2021-0496
26. Alves RCC, Ferreira RO, Frazão DR, de Souza Né YG, Mendes PFS, Marañón-Vásquez G, et al. The Relationship between Exercise and Salivary Oxidative Stress: A Systematic Review. *Antioxidants*. 2022 Jul 29;11(8):1489. doi:10.3390/antiox11081489
27. González D, Marquina R, Rondón N, Rodríguez-Malaver AJ, Reyes R. Effects of Aerobic Exercise on Uric Acid, Total Antioxidant Activity, Oxidative Stress, and Nitric Oxide in Human Saliva. *Research in Sports Medicine*. 2008 Jun 12;16(2):128–37. doi:10.1080/15438620802103700
28. Cheung K, Hume PA, Maxwell L. Delayed Onset Muscle Soreness. *Sports Medicine*. 2003;33(2):145–64. doi:10.2165/00007256-200333020-00005
29. Lindsey B, Shaul Y, Martin J. Salivary biomarkers of tactical athlete readiness: A systematic review. *PLoS One*. 2025 Apr 1;20(4 April). doi:10.1371/journal.pone.0321223 PubMed PMID: 40299918.
30. Stellingwerff T, Heikura IA, Meeusen R, Bermon S, Seiler S, Mountjoy ML, et al. Overtraining Syndrome (OTS) and Relative Energy Deficiency in Sport (RED-S): Shared Pathways, Symptoms and Complexities. *Sports Medicine*. Springer Science and Business Media Deutschland GmbH; 2021. p. 2251–80. doi:10.1007/s40279-021-01491-0 PubMed PMID: 34181189.
31. Kreher J. Diagnosis and prevention of overtraining syndrome: an opinion on education strategies. *Open Access J Sports Med*. 2016 Sep;Volume 7:115–22. doi:10.2147/oajsm.s91657
32. Fox JL, O'Grady CJ, Scanlan AT. The Relationships Between External and Internal Workloads During Basketball Training and Games. *Int J Sports Physiol Perform*. 2020 Sep 1;15(8):1081–6. doi:10.1123/ijsp.2019-0722
33. Vázquez-Guerrero J, Suarez-Arrones L, Casamichana Gómez D, Rodas G. COMPARING EXTERNAL TOTAL LOAD, ACCELERATION AND DECELERATION OUTPUTS IN ELITE BASKETBALL PLAYERS ACROSS POSITIONS DURING MATCH PLAY.
34. Haller N, Behringer M, Reichel T, Wahl P, Simon P, Krüger K, et al. Blood-Based Biomarkers for Managing Workload in Athletes: Considerations and Recommendations for Evidence-Based Use of

- Established Biomarkers. Sports Medicine. Springer Science and Business Media Deutschland GmbH; 2023. p. 1315–33. doi:10.1007/s40279-023-01836-x PubMed PMID: 37204619.
35. Fullagar HHK, Skorski S, Duffield R, Hammes D, Coutts AJ, Meyer T. Sleep and Athletic Performance: The Effects of Sleep Loss on Exercise Performance, and Physiological and Cognitive Responses to Exercise. Sports Medicine. Springer International Publishing; 2015. p. 161–86. doi:10.1007/s40279-014-0260-0 PubMed PMID: 25315456.
 36. NEVILLE V, GLEESON M, FOLLAND JP. Salivary IgA as a Risk Factor for Upper Respiratory Infections in Elite Professional Athletes. Med Sci Sports Exerc. 2008 Jul;40(7):1228–36. doi:10.1249/MSS.0b013e31816be9c3
 37. Castilho T, da Silva Guimarães L, Póvoa HCC, Antunes LS, Antunes LAA. Influence of physical exercises on salivary immunoglobulin A (sIgA) concentration in athletes: a systematic review with meta-analysis. Sport Sciences for Health. Springer-Verlag Italia s.r.l.; 2022. p. 621–39. doi:10.1007/s11332-021-00870-4
 38. McNair DM LMDLF. Manual for the Profile of Mood States. San Diego: Educational and Industrial Testing Service. 1971.

Supplementary Material and Methods

Correlation analysis

Kendall's rank correlation coefficients (τ) were calculated to examine monotonic associations within and between the biomarker, psychological, and physiological domains. For these analyses, athletes with 0 minutes of playing time were excluded so that correlations were evaluated only among athletes who had participated in the game. Additionally, associations between biomarkers and performance metrics were investigated. Kendall's τ was selected because of the limited sample size, and because several variables were ordinal, non-normally distributed, or potentially affected by outliers. Correlations were visualized using circos plots for within- and cross-domain associations (Figure 1) and heat maps for biomarker-performance associations (Figure 2). Only statistically significant correlations were displayed in Figure 1.

Stratification analysis

For stratification analyses, variables of interest were divided into three ordered groups, when possible, using tertiles to represent low, medium, and high levels. Physiological and psychological variables were stratified and salivary biomarker concentrations were compared across these groups. Differences across groups were evaluated using Kruskal–Wallis tests and group distributions were visualized using boxplots. This rank-based non-parametric procedure was selected because variables were not assumed to be normally distributed, and subgroup sizes were sometimes unequal. All combinations were tested; however, only statistically significant findings are presented in Figure 3.

Risk-enrichment analysis

To investigate whether specific psychophysical states were associated with an increased prevalence of biomarker abnormalities, a risk-enrichment analysis was performed. For each psychophysical variable, trait-positive subgroups were defined using predefined thresholds representing either high-risk elevated states (e.g., soreness, anger, tiredness ≥ 7 and ≥ 4) or high-risk reduced states (e.g., calmness, energy ≤ 3), while biomarker abnormalities were defined using within-sample standardized scores (z-scores), calculated as follows:

$$z = \frac{(X - \mu)}{\sigma}$$

where X represents the observed biomarker value, μ is the mean biomarker value across the dataset, and σ is the corresponding standard deviation.

Biomarker abnormalities were defined according to the magnitude and direction of standardized deviations. Elevated biomarker events were identified using thresholds of $z \geq 1.0$ and $z \geq 1.5$, corresponding to moderate and substantial positive deviations from the dataset mean, respectively. Reduced biomarker events were defined as $z \leq -1.0$, representing biologically meaningful decreases relative to the population average. These thresholds were selected to capture deviations exceeding approximately one standard deviation from the mean, a commonly adopted criterion for detecting atypical physiological responses in athlete monitoring research. Event rates, risk ratios (RR), risk differences, and odds ratios (OR) were calculated by comparing trait-positive participants with (i) the global event rate and (ii) the trait-negative event rate. Values greater than 1.0 or 1.5 indicated an increased likelihood of biomarker abnormalities within the psychophysical subgroup, whereas values less than 1.0 indicated a reduced likelihood.

Recovery phenotype analysis

To quantify subjective recovery, delta scores (Δ) were calculated for each questionnaire-derived variable as follows:

$$\Delta = \text{Recovery score} - \text{Post-game score}$$

The post-game score was the value reported by the athlete after a competitive game, whereas the recovery score was the value reported by the same athlete 2–3 days after that game. Thus, Δ represented the within-athlete change in each questionnaire variable from the immediate post-game assessment to the subsequent recovery-phase assessment. Positive or negative Δ values were interpreted according to the directionality of the construct. For variables in which lower scores reflected improvement (e.g., tiredness, anger), more negative Δ values indicated greater recovery, whereas for variables in which higher scores reflected improvement (e.g., energy level, calmness), more positive Δ values indicated greater recovery. For group-based analyses, athletes were categorized into fast and slow recoverers using a median-split approach applied to the Δ scores. Observations showing greater improvement than the median value were classified as fast recoverers, whereas those exhibiting less improvement than the median were classified as slow recoverers. Biomarkers demonstrating the largest differences between recovery phenotypes were compared using two-sided Mann–Whitney U tests. Results were presented as boxplots showing medians, interquartile ranges, and individual observations.

Linear mixed-effects models

To examine whether associations between subjective recovery changes and biomarkers depended on match exposure²⁶, linear mixed-effects models were fitted with athletes as a random intercept. Three linear mixed-effects models were fitted for each questionnaire parameter and biomarker combination, in three steps. Prior to all model fitting, recovery biomarker values were standardized as z-scores to facilitate comparison across biomarkers measured on different scales. Consequently, model coefficients (β) represented the expected change in standardized biomarker concentration associated with a one-unit increase in questionnaire Δ score. For each questionnaire–biomarker combination, an unadjusted Δ -only model was first fitted, followed by a model adjusted for minutes played and a model including a Δ score $\times$ minutes played interaction term.

Δ -only model

Firstly, an unadjusted Δ -only linear mixed-effects model was fitted to examine whether the magnitude of change in each questionnaire parameter was associated with recovery biomarker concentrations. In this model, the previously calculated questionnaire Δ score was included as the only fixed-effect predictor, and athlete was

included as a random effect to account for repeated observations within athletes. This model was expressed in simplified form as:

$$\text{Recovery biomarker z-score} = \beta\Delta(\Delta \text{ score}) + \text{athlete random effect}$$

The $\beta\Delta$ coefficient from this model represented the association between the questionnaire Δ score and the standardized recovery biomarker concentration before adjustment for match exposure.

Model adjusted for minutes played

Secondly, minutes played were added as a continuous covariate to account for differences in match exposure and workload. This model examined whether the association between questionnaire Δ scores and recovery biomarker concentrations remained after adjustment for playing time. This model was expressed in simplified form as:

$$\text{Recovery biomarker z-score} = \beta\Delta(\Delta \text{ score}) + \beta_{\text{min}}(\text{minutes played}) + \text{athlete random effect}$$

The $\beta\Delta$ coefficient from this model represented the association between subjective recovery change and standardized recovery biomarker concentration after accounting for minutes played.

Model with $\Delta \times$ minutes played interaction term

Thirdly, a $\Delta \times$ minutes played interaction model was employed to assess whether the relationship between subjective recovery change and biomarker concentration varied according to playing time. This model was fitted as follows to determine whether the association between questionnaire Δ scores and recovery biomarker concentrations varied according to playing time:

$$\text{Recovery biomarker z-score} = \beta\Delta(\Delta \text{ score}) + \beta_{\text{min}}(\text{minutes played}) + \beta_{\text{int}}(\Delta \text{ score} \times \text{minutes played}) + \text{athlete random effect}$$

For this interaction model, the β coefficient of the Δ score $\times$ minutes played term represented whether the Δ score–biomarker association changed with each additional minute played.

Match exposure was also examined using categorical classifications. Athletes were categorized as Did Not Play (DNP) if they recorded 0 minutes and Played if they accumulated more than 0 minutes of game time. Playing time was also divided into Low Minutes ($0 < \text{LM} \leq 23.0$) and High Minutes ($\text{HM} > 23.0$) groups based on the median playing time (23.0 minutes) among athletes who participated in competition. Differences in questionnaire Δ scores across the three minutes-played groups were evaluated using Kruskal–Wallis tests. This analysis was used to determine whether subjective recovery changes differed according to match exposure.

Analysis of variance (ANOVA and MANOVA) / Performance group analysis

To examine differences in psychobiophysical characteristics according to performance profile, observations were categorized into good- and poor-performance readiness groups based on PIR/min and self-score. PIR/min was used as an objective performance metric, whereas self-score reflected the athlete's subjective perception. For each variable, the median value was used as the classification threshold. Observations with both PIR/min and self-score above the median were classified as good performance, whereas observations with both PIR/min and self-score below the median were classified as poor performance. Observations with discordant classifications, in which one measure was above and the other below its median, were excluded from the group-comparison analyses to maximize the distinction between performance profiles. Differences in the overall psychobiophysical profile between good- and poor-performance-readiness observations were examined using multivariate analysis of variance (MANOVA), which accounted for correlations among the dependent variables. Follow-up univariate ANOVAs were then performed to examine group differences in individual

athlete-reported variables and salivary biomarkers. To control for multiple comparisons, Holm-adjusted p-values were calculated.

Because repeated observations were collected from the same athletes across the competitive season, observations were not fully independent and were nested within players. Where possible, conclusions were prioritized from models that accounted for within-athlete clustering.