Physical Education Theory and Methodology
Теорія та методика фізичного виховання

ISSN 1993-7989 (print)
ISSN 1993-7997 (online)
ISSN-L 1993-7989

Original Scientific Articles. Training Effects and Experimental Design

Effect of Training Load and Recovery Time on Neuromuscular Performance in Elite Youth Soccer Players

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Authors' Contribution: A – Study design; B – Data collection; C – Statistical analysis; D – Manuscript Preparation; E – Funds Collection

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Accepted for Publication: June 06, 2026
Published: July 27, 2026

DOI: 10.17309/tmfv.2026.4.11

Abstract

Background. Managing training load and recovery in developing elite footballers is a major challenge for optimizing performance while limiting the risk of neuromuscular fatigue. Vertical jump with countermovement (VJM) remains a preferred indicator of neuromuscular status, but recovery kinetics after microcycles of contrasting intensity remain insufficiently documented in young athletes.

Objectives. To examine the impact of training load and recovery time on neuromuscular performance by analyzing the modulating effects of microcycle type, age category, and acute-to-chronic workload ratio (ACWR).

Materials and Methods. Seventy-five elite male footballers (U16-U18) participated in a six-month longitudinal protocol including CMJ assessments before and 24 h and 48 h after moderate- and high-intensity microcycles. Linear mixed models were used to analyze main effects and interactions.

Results. Significant effects were observed for microcycle type ($F = 69.93$, $p < 0.001$), measurement time ($F = 374.48$, $p < 0.001$), and ACWR ($F = 7.41$, $p = 0.007$). High-intensity microcycles induced greater decreases in CMJ performance at 24 h ($\beta = -1.072$, $p < 0.001$), followed by partial recovery at 48 h. ACWR was strongly correlated with CMJ changes at 24 h ($r = -0.766$, $p < 0.001$).

Conclusion. A critical window of neuromuscular fatigue exists 24 h after a microcycle, modulated by training intensity and workload context, supporting the value of systematic neuromuscular monitoring following high-intensity microcycles.

Keywords: neuromuscular fatigue, countermovement jump, training load, acute-to-chronic workload ratio, young footballers, recovery.

Introduction

Training load management is a major challenge in modern soccer, where congested competition schedules force elite players to compete in more than 60 matches per season with limited recovery windows. Consequently, finding the optimal balance between applying sufficient training stimuli to induce physiological adaptations and preventing excessive fatigue accumulation is a central concern for coaching staff (West et al., 2021). This issue is particularly critical for reducing the risk of non-contact injuries, which are often associated with acute peaks in training load or chronic inadequate preparation (Malone et al., 2017a). Therefore, longitudinal monitoring of neuromuscular responses to training loads allows for the early identification of fatigue states and the adjustment of training programs accordingly (Evans et al., 2022). However, the temporal kinetics of recovery and its modulation by training load intensity remain insufficiently documented, especially in developing populations. Moreover, developing elite footballers (U16-U18) exhibit specific physiological characteristics that make training load management a complex task.

This period coincides with major biological transformations linked to pubertal maturation, including changes in body composition, force production capacity, and the mechanical properties of the musculo-tendinous system (García-Santamaría et al., 2024; Wenger & Csapo, 2025). Although biological maturation status is a key determinant of load tolerance, the present study relies on chronological age as a developmental indicator. This methodological choice is based on the logistical feasibility of longitudinal follow-up in an applied context and the systematic availability of this variable in soccer academies, while recognizing that this approach does not fully capture inter-individual maturational heterogeneity. Nevertheless, considerable variability in maturation status at identical chronological ages generates substantial heterogeneity in injury susceptibility, with biologically less mature players demonstrating increased vulnerability when exposed to loads comparable to those of their more developmentally advanced peers (Gundersen et al., 2022). Elite soccer academies impose dense competition and training schedules during this critical phase, making it imperative to implement robust, individualized monitoring strategies to optimize the load-adaptation-recovery continuum (Hannon et al., 2021).

The countermovement jump (CMJ) test has established itself as a reference tool for quantifying neuromuscular performance and detecting residual fatigue in team sports (R. Gathercole et al., 2015). Indeed, its non-invasiveness, logistical feasibility, short administration time, and proven sensitivity to training- and competition-induced alterations in neuromuscular function make it particularly suitable for the longitudinal monitoring of young athletes (Silva et al., 2021). The CMJ evaluates the capacity of the stretch-shortening cycle (SSC), a fundamental mechanism underlying explosive soccer actions such as sprints, changes of direction, and jumps (Falces-Prieto et al., 2022). Variations in jump height reflect the functional state of peripheral (muscle contractility, tendon elastic properties) and central (corticospinal excitability, recruitment strategies) components of the neuromuscular system, enabling an integrative assessment of fatigue (Muñoz-Gracia et al., 2025). Small to moderate reductions in CMJ performance (ES = -0.38 to -0.42) have been documented within 12 to 24 hours after matches in footballers, with a trend toward partial recovery at 48 hours, confirming its validity as a marker of recovery (Akyildiz et al., 2022).

However, the majority of previous studies have adopted cross-sectional designs or focused on adult populations, limiting the generalizability of their findings to young elite players. The temporal dynamics of neuromuscular recovery are a crucial parameter for rational training planning, particularly in microcycles in which several high-intensity sessions must be scheduled (Clemente et al., 2025). The 24- and 48-hour post-exercise windows represent critical decision points: at 24 hours, neuromuscular fatigue generally reaches its peak, whereas at 48 hours, partial recovery is expected, although its magnitude remains influenced by the initial training load (Evans et al., 2022). Understanding precisely how microcycle intensity (moderate versus high) modulates these recovery kinetics would make it possible to optimize session spacing and individualize the required recovery periods. High-load microcycles, characterized by greater training volumes and intensities, induce more pronounced and prolonged neuromuscular disturbances than moderate microcycles, but precise quantitative data for elite young footballers remain scarce (Martin-Garetxana et al., 2024). The potential interaction between microcycle type, recovery time, and age category has not been systematically explored using appropriate analytical models that account for the hierarchical structure of longitudinal data.

Integrated quantification of training load via complementary internal and external methods is a recommended practice in contemporary soccer (West et al., 2021). Subjective effort perception (session-RPE) offers a global estimate of internal load, while global positioning systems (GPS) and accelerometry provide objective data on external mechanical load (Benson et al., 2020). The Acute:Chronic Workload Ratio (ACWR) has emerged as a contextualized indicator for relating recent training load to chronic exposure (Malone et al., 2017a). However, the use of ACWR is the subject of substantial methodological debate because of several fundamental limitations. First, the inherent mathematical coupling between the numerator and denominator (the acute workload being included in the calculation of the chronic workload) introduces an artificial statistical dependence that can confound associations with outcome variables.

Secondly, the debate over the use of ratios versus differences has highlighted that ACWR does not adequately normalize the acute workload relative to the chronic workload, making its interpretation ambiguous. Thirdly, the optimal time windows for calculating acute (7 days) and chronic (21–28 days) workloads, as well as the calculation methods (moving averages versus exponentially weighted moving averages), remain controversial. Several authors have recently questioned the causal validity of ACWR for predicting injury risk, arguing that the observed associations may reflect methodological artifacts rather than true prognostic relationships. Despite these critical considerations, ACWR remains a potentially relevant heuristic tool when integrated into a multimodal monitoring approach, particularly when examined in conjunction with direct measures of neuromuscular performance such as the CMJ (Bowen et al., 2017). Despite the accumulation of knowledge, several substantial gaps remain. First, the majority of studies have adopted cross-sectional designs, limiting the understanding of individual longitudinal recovery trajectories (Wiewelhove et al., 2024).

No investigation has simultaneously examined the influence of microcycle type (moderate versus high), recovery time (baseline, 24 h, 48 h), and chronological age category (U16, U17, U18) on neuromuscular performance using appropriate statistical models that account for repeated measures. This specific combination of factors in a controlled longitudinal design represents a novel contribution beyond the work of Martin-Garetxana et al. (2024), which did not simultaneously integrate these three temporal and developmental dimensions. Thirdly, the application of linear mixed models, which account for the dependence of intra-individual observations and explicitly model fixed and random effects, remains underutilized in this field of research (Connolly et al., 2024). Fourthly, the time-specific predictive ability of ACWR for 24- and 48-hour changes in CMJ performance, as well as the magnitude of these associations, has not been systematically quantified in elite youth footballers despite the methodological controversies surrounding this indicator.

Finally, the practical implications for individualized training planning according to developmental status require empirical documentation. To address these gaps, this study aims to examine the impact of training load and recovery time on neuromuscular performance, as assessed by the CMJ, in developing elite footballers. A longitudinal design was adopted and analyzed using linear mixed models, allowing the hierarchical and repeated structure of the data to be taken into account. Specifically, the study aims to analyze the temporal evolution of CMJ performance at baseline and 24 and 48 hours after moderate- and high-load microcycles; to compare the kinetics of neuromuscular recovery among the U16, U17, and U18 chronological age categories; to examine the association between ACWR and changes in CMJ performance at different measurement time points; and to identify predictive factors (ACWR, total load, RPE, age, category, and microcycle type) associated with changes in neuromuscular performance at 24 and 48 hours after the microcycle.

Materials and Methods

This study adopted a within-subjects, repeated-measures design. Specifically, Each player was assessed at three time points (baseline, 24 h and 48 h post-microcycle) in two conditions corresponding to a moderate-load microcycle (MOD) and a high-load microcycle (HIGH), generating six measures of neuromuscular performance (CMJ) per participant (2 microcycles × 3 time points). The two microcycles were conducted during the competitive season and separated by a minimum interval of three weeks. Furthermore, the order of exposure to MOD and HIGH conditions was counterbalanced between participants. Although The microcycles had a comparable structure (4-5 sessions over 7 days) but differed intentionally in terms of internal and external load.

In this context, HIGH microcycles corresponded to weeks characterized by high acute load (ACWR ≥ 1.3), associated with higher volumes of total distance and accelerations, while MOD microcycles corresponded to acute loads between 0.8 and 1.3 of the individual chronic load. Importantly, The classification of microcycles was based on the weekly planning of the technical staff and was validated a posteriori by analysis of the recorded loads. All evaluations were carried out in a standardized training environment. Players followed a common weekly program within their age category.

Study Participants

Seventy-five (n = 75) elite male footballers in the training phase were included in this study and divided into three chronological age categories: U16 (n = 25; age: 15.4 ± 0.5 years; body mass: 63.2 ± 7.8 kg; height: 172.5 ± 6.3 cm), U17 (n = 24; age: 16.5 ± 0.4 years; body mass: 67.1 ± 8.2 kg; height: 176.2 ± 5.9 cm) and U18 (n = 26; age: 17.6 ± 0.5 years; body mass: 71.3 ± 7.5 kg; height: 178.9 ± 6.1 cm). All participants played for a professional soccer club at national level and had a minimum of five years' structured playing experience, including organized club training. To characterize developmental status, the players' biological maturation was estimated retrospectively using the maturity offset (years from peak statural growth velocity, PHV), calculated according to the regression equation proposed by (Monasterio et al., 2024) integrating chronological age and body size. This indirect approach, widely used in applied contexts where direct assessment of maturation is not feasible, provides a continuous estimate of individual maturational status. Descriptive analyses revealed a progressive increase in offset maturity with chronological age, with mean values of 1.40 ± 0.37 years in U16s, 2.02 ± 0.42 years in U17s and 2.79 ± 0.43 years in U18s, indicating that the majority of players were in the post-PHV phase. These results confirm the existence of differences in biological maturation between age categories, while also highlighting inter-individual variability within each group (Table 1).

Biological Maturation Characteristics

Descriptive analysis of biological maturation revealed a progressive increase in maturity offset across age categories. Mean maturity offset values were 1.40 ± 0.37 years in U16 players, 2.02 ± 0.42 years in U17 players, and 2.79 ± 0.43 years in U18 players, indicating that the majority of players were post–peak height velocity. These results confirm substantial inter-category differences in biological maturation status within the sample.

Inclusion and Exclusion Criteria

Inclusion criteria included: (1) regular participation in training and competitions during the study period, (2) absence of musculoskeletal injury limiting full-intensity practice during the three months prior to inclusion, and (3) absence of medical contraindication to intensive sports practice. Exclusion criteria included less than

Table 1. Biological maturation characteristics by age category (maturity offset, years from PHV)

Variable	U16 (n = 25)	U17 (n = 24)	U18 (n = 26)
Maturity offset (years from PHV), mean ± SD	1.40 ± 0.37	2.02 ± 0.42	2.79 ± 0.43
Median [IQR]	1.39 [1.16–1.63]	1.92 [1.72–2.31]	2.91 [2.61–3.14]
Min–Max	0.69–2.11	1.44–3.19	1.91–3.35

Note. Maturity offset (years from peak height velocity, PHV) was retrospectively estimated from chronological age and standing height using a regression-based prediction model. Positive values indicate post-PHV maturation status. Descriptive statistics are reported per player (baseline values only).

90% participation in scheduled training sessions, or the occurrence of an injury resulting in prolonged unavailability incompatible with longitudinal follow-up.

This 90% threshold was chosen to guarantee sufficient and homogeneous exposure to the micro-training cycles analyzed, a necessary condition for valid interpretation of neuromuscular responses to imposed loads. Over the entire investigation period, the average rate of participation in the training sessions was 93.4 ± 4.1%, with no difference between age categories. During follow-up, no participant was excluded from the final analysis due to major injury. Players with transient discomfort or short-term unavailability (≤ 7 days) returned to full training after recovery, and their data were retained in the analyses. No partial data censoring was applied, and all 75 participants initially recruited were included in the final analyses.

The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and received approval from the local institutional ethics committee. Written informed consent was obtained from all participants, and from their legal representatives in the case of minors. A prior information meeting was organized with the players and their parents to present the objectives, procedures, expected benefits and potential risks associated with participation. Participants were informed of their right to withdraw from the study at any time, without justification or consequence. A two-week familiarization period preceded data collection in order to limit learning effects, particularly for neuromuscular performance assessments and the use of the perception of effort scale.

Measuring Instrument

Assessment of Neuromuscular Performance

Countermovement jump (CMJ): Neuromuscular performance was assessed using the countermovement vertical jump (CMJ) test, widely recognized as a valid and sensitive indicator of neuromuscular status and training-induced fatigue in team sports athletes (R. Gathercole et al., 2015). Jumps were performed using a Chronojump Boscosystem contact platform (version 1.6.2, Barcelona, Spain). The validity of this tool was demonstrated by near-perfect correlation with reference force platforms (r ≈ 0.99), as well as excellent intra-device reliability (coefficient of variation < 5%) for jump height measurement (Pueo et al., 2020). Participants performed the test with feet shoulder-width apart, hands on hips to eliminate upper limb contribution. After a standardized 10-minute warm-up, three maximal trials were performed, separated by 60 seconds of passive recovery. The best performance (jump height in cm) among the three trials was retained for analysis, in line with methodological recommendations (R. Gathercole et al., 2015) in accordance with standard protocols. Testing occurred consistently between 09:00–11:00 to minimize circadian effects.

Quantifying Drive Load

Internal training load was quantified with the session-rating of perceived exertion (sRPE) method, using Foster's modified CR-10 scale (Foster et al., 2001). Approximately 20 minutes after each session, players individually answered the question: "How would you rate the overall difficulty of this session?", on a scale ranging from 0 (rest) to 10 (maximum effort). The internal load for each session was calculated by multiplying the RPE score by the session duration (sRPE = RPE × duration, in arbitrary units). This method is widely validated in footballers, with strong correlations with physiological markers and heart rate-based methods (Impellizzeri et al., 2020).

External training load was measured using Catapult Sports® global positioning systems (GPS), model OptimEye S5 (Catapult Sports, Melbourne, Australia), sampling at 10 Hz, with integrated triaxial accelerometers at 100 Hz. The validity and reliability of this device for analyzing locomotor demands in soccer have been widely documented (Akyildiz et al., 2024; Kielė & Solianik, 2023). Each player wore the same GPS unit throughout the study to limit inter-unit variability. Variables analyzed included total distance covered (m), number of accelerations > 2 $m{\cdot}s^{-2}$ and number of high-intensity accelerations > 3 $m{\cdot}s^{-2}$. Data were processed with proprietary OpenField™ software (Catapult Sports), using the manufacturer's standard filtering algorithms, in accordance with the methodological recommendations for the analysis of GPS data in soccer.

Acute-to-chronic Workload Ratio (ACWR)

The acute-to-chronic workload ratio (ACWR) was calculated to contextualize each player's recent workload versus chronic exposure. Acute workload was defined as the current week's total training load (sRPE) (7 days), while chronic workload was defined as the moving average of the previous four weeks (28 days). ACWR was calculated according to the following formula: ACWR = acute load / chronic load, using a coupled rolling average, a method commonly employed in the soccer literature (Pinelli et al., 2025a). ACWR values were interpreted according to the classically proposed thresholds: < 0.8 (underexposure), 0.8-1.3 (optimal zone), 1.3-2.0 (preparation zone) and > 2.0 (increased risk zone) (Qin et al., 2025a).

Although maturity offset (years from peak growth velocity, PHV) was estimated for descriptive purposes to characterize the developmental profile of the sample, it was not incorporated into the main inferential models for two reasons. Firstly, the study was designed and scaled around the grouping strategy applied in elite soccer academies (U16-U18 categories), making chronological age category the most ecologically valid decision variable for practitioners. Secondly, as maturity offset is mathematically derived from age and body size, it exhibits substantial overlap with chronological age and/or age category in predominantly post-PHV samples, which may introduce redundancy and collinearity in multivariate models. Consequently, offset maturity was reported to describe the sample and inform interpretation of the results, while chronological age category was retained as the main developmental factor in inferential analyses.

Ethical Considerations

This study was conducted in accordance with the ethical principles outlined in the Declaration of Helsinki for research involving human participants. All procedures were designed to ensure the safety, well-being, and rights of the participants throughout the study. Prior to inclusion, all players and their legal guardians (for minors) received detailed information regarding the study objectives, procedures, expected benefits, and potential risks. Written informed consent was obtained from all participants and their legal guardians before data collection.

Participation in the study was entirely voluntary, and participants were informed of their right to withdraw at any time without any consequences. The collected data were anonymized and handled confidentially in accordance with applicable data protection regulations.

The procedures implemented (countermovement jump testing and training load monitoring) are non-invasive and commonly used in sports science, thus presenting minimal risk to participants.

Statistical Analysis

All statistical analyses were performed with significance set at $p < 0.05$ using SPSS software, version 27.0.1.0. Descriptive statistics are presented as means ± standard deviation and 95% confidence intervals. The effect of microcycle type (moderate vs. high), recovery time (baseline, 24 h, 48 h), age category (U16, U17, U18) and acute-to-chronic workload ratio (ACWR) on neuromuscular performance (CMJ) was examined using a linear mixed model, including a random intercept per participant to account for intra-individual repeated measures. Degrees of freedom were estimated using the Satterthwaite method. In the presence of significant effects, post-hoc comparisons were made using estimated marginal means (EMM), with Bonferroni adjustment for multiple comparisons. Separate multiple linear regressions were used to identify predictors of variations in CMJ performance at 24 h and 48 h post-microcycle. Models included ACWR, total training load, mean RPE, age category and microcycle type. Regression coefficients, fit indices (R^2, adjusted R^2) and root mean square error (RMSE) were reported. Pearson correlations were calculated to examine associations between load indicators and CMJ performance variations. Sensitivity analyses related to collinearity between ACWR and total load are presented in supplementary material.

Results

The results are organized to describe the evolution of neuromuscular performance according to microcycle type, recovery time, and age category. The effect of moderate and high-load microcycles is examined based on variations in CMJ height measured at rest, then 24 and 48 hours after training, taking into account the load context represented by the ACWR. Comparisons between conditions allow us to characterize the kinetics of fatigue and recovery, as well as the differences observed between the U16, U17, and U18 categories. Finally, the association between training load indicators and CMJ variations is explored in order to identify the factors most closely related to short- and medium-term alterations in neuromuscular performance.

Effects of Training Load and Recovery Time on CMJ Performance

Descriptive statistics for countermovement jump (CMJ) height across experimental conditions are summarized in Table 2. The analysis included 450 total observations with no missing values. When examining main effects, CMJ height increased with age category, with U18 players demonstrating the highest mean performance (38.82 ± 3.29 cm), followed by U17 (36.27 ± 3.33 cm) and U16 players (33.30 ± 3.53 cm). Regarding recovery kinetics, CMJ performance was highest at baseline (38.21 ± 3.02 cm), decreased substantially at 24 h post-training (34.30 ± 4.41 cm), and showed partial recovery at 48h (35.99 ± 3.70 cm). High-load microcycles resulted in significantly lower CMJ values (34.20 ± 4.03 cm) compared to moderate-load microcycles (38.13 ± 3.04 cm), reflecting the differential neuromuscular impact of training intensity.

Table 2. Descriptive statistics for Countermovement Jump (CMJ) height across experimental factors

Factor	Level	n	Mean ± SD (cm)	95% CI
Category	U16	150	33.30 ± 3.53	[32.73, 33.87]
	U17	144	36.27 ± 3.33	[35.72, 36.82]
	U18	156	38.82 ± 3.29	[38.30, 39.34]
Timepoint	Baseline	150	38.21 ± 3.02	[37.72, 38.70]
	24h Post	150	34.30 ± 4.41	[33.59, 35.01]
	48h Post	150	35.99 ± 3.70	[35.39, 36.58]
Microcycle Type	High	225	34.20 ± 4.03	[33.67, 34.73]
	Moderate	225	38.13 ± 3.04	[37.73, 38.53]
Overall	Total	450	36.16 ± 4.07	[35.78, 36.54]

Note. SD = Standard Deviation; CI = Confidence Interval; n = number of observations. Data represent raw CMJ height measurements before statistical modeling. The sample size per cell in the complete factorial design (3 Categories × 2 Microcycle Types × 3 Timepoints) is 25 observations.

To further investigate these preliminary observations, linear mixed models were employed to account for repeated measures and examine the independent and interactive effects of microcycle type, recovery timepoint, age category, and ACWR on CMJ performance. This approach allows us to move beyond descriptive statistics and assess the statistical significance of observed differences while controlling for inter-individual variability.

The results of the linear mixed model analysis are presented in Table 3 and Table 4. A significant main effect was found for ACWR, Microcycle Type, Timepoint, and Category (all $p < .001$). Crucially, a significant two-way interaction was observed between Microcycle Type and Timepoint ($F_{(2, 214.53)} = 138.45$, $p < .001$). No other interactions (Microcycle Type × Category, Timepoint × Category, or the three-way interaction) were statistically significant (all $p > .34$).

Post-hoc examination of the significant interaction (Table 3) revealed that the negative effect of a high-load microcycle on CMJ height was most pronounced at the 24-hour post-training timepoint (interaction term: $\beta = -1.07$, $t_{(214.53)} = -13.88$, $p < .001$), indicating a more severe and prolonged neuromuscular fatigue compared to a moderate-load microcycle. By 48 hours, the difference in CMJ performance between microcycle types was no longer significant (interaction term: $\beta = -0.08$, $p = .315$). Furthermore, a higher ACWR was independently associated with lower CMJ performance ($\beta = -1.77$, $p = .007$). The model included a random intercept for each participant ('ID') to account for baseline inter-individual variability. Random slopes for the Microcycle Type Timepoint interaction could not be reliably estimated due to constraints in the data structure and were therefore omitted from the final model to ensure convergence and stability of the estimates.

Table 3. Analysis of fixed effects from the linear mixed model on Countermovement Jump (CMJ) height

Effect	df_num	df_den	F	p
ACWR	1	198.66	7.412	.007
Microcycle Type	1	191.47	69.930	< .001
Timepoint	2	77.29	374.481	< .001
Category	2	71.90	65.698	< .001
Microcycle Type × Timepoint	2	214.53	138.445	< .001
Microcycle Type × Category	2	124.19	0.856	.427
Timepoint × Category	4	77.29	1.044	.390

Note. df_num = numerator degrees of freedom; df_den = denominator degrees of freedom (Satterthwaite method). Significant effects (p < .05) are highlighted in bold. The model included ACWR as a continuous covariate, Microcycle Type (Moderate, High), Timepoint (Baseline, 24h, 48h), and Category (U16, U17, U18) as fixed factors, and a random intercept for participant ID.

Building on the results of the mixed model analysis, estimated marginal means were calculated to visualize the temporal evolution of CMJ performance across microcycle types and age categories. These estimates provide a clearer understanding of the magnitude and direction of neuromuscular fatigue and recovery, and facilitate interpretation of practical differences between conditions.

Temporal Evolution of Neuromuscular Performance as a Function of Age, Training Load, and Microcycle Type

Estimated marginal means demonstrated a progressive increase in CMJ performance across age categories, with U16 players exhibiting the lowest values and U18 players the highest across all conditions. Within each age category, moderate-load microcycles consistently yielded higher estimated marginal mean values compared to high-load microcycles at all measurement timepoints. At 24 hours post-training, the difference between moderate- and high-load conditions was most pronounced across all age groups (U16: Δ = 5.15 cm; U17: Δ = 5.14 cm; U18: Δ = 5.15 cm). For high-load microcycles, the lowest CMJ values were observed at 24 hours post-training (U16: 28.72 ± 0.42 cm; U17: 31.84 ± 0.43 cm; U18: 34.50 ± 0.42 cm), followed by partial recovery at 48 hours and near-complete recovery at baseline. Standard errors remained consistent across conditions (SE ≈ 0.42), indicating stable precision of the estimated values throughout the model. The significant main effect of age category observed in the model should be interpreted with caution, as the classification was based on chronological age and may, at least in part, reflect underlying inter-individual differences in biological maturation status rather than the effect of chronological age per se.

Building on the patterns observed in the estimated marginal means, multiple linear regression models were developed to predict CMJ changes at 24 and 48 hours post-microcycle. This approach allows us to quantify the relative contributions of ACWR, training load, perceived exertion, age category, and microcycle type to neuromuscular performance recovery, moving beyond descriptive observations to predictive analysis.

Prediction of CMJ Recovery at 24 and 48 h Following Training Microcycles

The multiple linear regression model predicting CMJ changes at 24 hours post-microcycle (M_1) explained 65.6% of the variance ($R^2 = 0.656$, adjusted $R^2 = 0.651$), with a root mean square error of 1.659 cm. The model demonstrated strong predictive capacity (R = 0.81), indicating that the combination of ACWR, training load, RPE, age, category, and microcycle type accounted for a substantial proportion of neuromuscular performance changes at this timepoint. For CMJ changes at 48 hours post-microcycle, the null

Table 4. Parameter estimates for key fixed effects from the linear mixed model

Parameter	Estimate(β)	SE	df	t	p
Intercept	38.372	0.847	214.95	45.316	< .001
ACWR	-1.771	0.651	198.66	-2.722	.007
Microcycle Type (High vs. Ref.)	-1.504	0.180	191.47	-8.362	< .001
Timepoint (24h vs. Baseline)	-1.870	0.092	72.96	-20.393	< .001
Timepoint (48h vs. Baseline)	-0.180	0.091	77.91	-1.985	.051
Category (U16 vs. Ref.)	-2.826	0.281	71.89	-10.057	< .001
Category (U17 vs. Ref.)	0.131	0.284	71.91	0.460	.647
Microcycle Type (High) × Timepoint (24 h)	-1.072	0.077	214.53	-13.881	< .001
Microcycle Type (High) × Timepoint (48 h)	-0.078	0.077	214.53	-1.006	.315

Legend. SE = Standard Error; df = denominator degrees of freedom. Factors were sum-coded. The Intercept represents the estimated grand mean of CMJ height (cm). The reference levels (Ref.) for the contrasts are the overall means across factor levels. For clarity, only parameters for significant main effects and the significant interaction are shown; non-significant higher-order interaction terms (involving Category) are omitted. The estimates for Microcycle Type and Timepoint represent the deviation of the «High» level and the post-training timepoints from the grand mean, respectively. The negative estimate for the interaction term (Microcycle Type (High) × Timepoint (24 h)) indicates a greater decrease in CMJ performance 24 hours after a high-load microcycle.

Table 5. Estimated marginal means of countermovement jump height according to age category, microcycle type, and recovery timepoint

Category	Microcycle	Timepoint	EMM (cm)	SE	95% CI Lower	95% CI Upper
U16	HIGH	24 h	28.72	0.422	27.89	29.55
	MOD	24 h	33.87	0.422	33.04	34.70
	HIGH	48 h	31.55	0.422	30.73	32.38
	MOD	48 h	34.72	0.422	33.89	35.55
	HIGH	Baseline	35.12	0.422	34.29	35.95
	MOD	Baseline	35.84	0.422	35.01	36.67
U17	HIGH	24 h	31.84	0.427	31.00	32.67
	MOD	24 h	36.98	0.431	36.14	37.83
	HIGH	48 h	34.39	0.427	33.55	35.23
	MOD	48 h	37.56	0.431	36.71	38.40
	HIGH	Baseline	38.04	0.427	37.20	38.88
	MOD	Baseline	38.76	0.431	37.92	39.60
U18	HIGH	24 h	34.50	0.417	33.69	35.32
	MOD	24 h	39.65	0.414	38.84	40.46
	HIGH	48 h	37.16	0.417	36.34	37.98
	MOD	48 h	40.32	0.414	39.51	41.14
	HIGH	Baseline	40.30	0.417	39.48	41.12
	MOD	Baseline	41.02	0.414	40.21	41.83

Legend. EMM = estimated marginal means; SE = standard error; CI = confidence interval; MOD = moderate-load microcycle; HIGH = high-load microcycle. Estimated marginal means were adjusted for acute:chronic workload ratio as covariate. U16, U17, and U18 represent age categories of elite youth soccer players. All values are expressed in centimeters.

model (M_0) explained no variance, whereas the full model (M_1) accounted for 36.7% of the variance ($R^2 = 0.367$, adjusted $R^2 = 0.357$, RMSE = 1.672 cm). The moderate predictive capacity observed at 48 hours (R = 0.61) suggests greater inter-individual variability in recovery patterns compared with the 24-hour timepoint, with predictor variables explaining a smaller proportion of differences in neuromuscular performance restoration. Due to the conceptual collinearity between chronological age and age category, the results of the regression models are presented based on the model including age category as the primary developmental indicator.

Table 6. Model fit indices for multiple linear regression models predicting countermovement jump changes at 24h and 48h post-microcycle

Outcome	Model	R	R^2	Adjusted R^2	RMSE
ΔCMJ_24 h	M_1	0.810	0.656	0.651	1.659
ΔCMJ_48 h	M_0	0.000	0.000	0.000	2.086
ΔCMJ_48 h	M_1	0.606	0.367	0.357	1.672

Legend. ΔCMJ_24h = change in countermovement jump height from baseline to 24 hours post-microcycle; ΔCMJ_48h = change in countermovement jump height from baseline to 48 hours post-microcycle; M_0 = null model (intercept only); M_1 = full model including acute:chronic workload ratio, training load (arbitrary units), mean rating of perceived exertion, chronological age, age category, and microcycle type as predictors; R = multiple correlation coefficient; R^2 = coefficient of determination; Adjusted R^2 = adjusted coefficient of determination; RMSE = root mean square error (expressed in centimeters).

To further ensure the robustness of these predictive findings, a sensitivity analysis was conducted by including chronological age as a proxy covariate for biological maturation. This step verifies whether the main effects identified in the regression models remain consistent when accounting for inter-individual differences in developmental status.

Sensitivity Analysis: Inclusion of Age as a Proxy Covariate for Biological Maturation

To address concerns regarding the integration of biological maturation in our models, a sensitivity analysis was performed by including chronological age as a proxy covariate for maturation in the linear mixed models for CMJ recovery at 24 and 48 hours. This approach allows us to verify whether the main effects observed for microcycle intensity, ACWR, and age category remain robust when accounting for individual variability related to maturation.

To extend the evaluation of recovery dynamics beyond sensitivity analyses, we next examined the differential predictive ability of regression models for CMJ changes at 24 and 48 hours post-microcycle. This approach enables a quantitative assessment of how the combination of ACWR, training load, RPE, age, category, and microcycle type explains variance in neuromuscular performance, and highlights the relative contribution of each predictor over time.

Building on the results from the regression models, further analyses including ANOVA and bivariate correlations were conducted to clarify the relationships between training load variables and CMJ changes. These analyses provide insight into the time-dependent effects of workload metrics,

Table 7. Sensitivity analysis: inclusion of age as a proxy covariate for biological maturation in linear mixed models for CMJ at 24 h and 48 h post-microcycle

Timepoint	Variable	Coefficient (Coef.)	p-value	Interpretation
24 h	Microcycle MOD vs HIGH	3.839	<0.001	Moderate microcycles result in better recovery → significant effect
	ACWR	-4.284	<0.001	High ACWR reduces CMJ → significant effect
	Category U17 vs U16	4.646	<0.001	U17 recover better than U16 → significant effect
	Category U18 vs U16	8.780	<0.001	U18 recover even better → significant effect
	Age	-1.449	0.147	Not significant → age does not alter main conclusions
48 h	Microcycle MOD vs HIGH	4.066	<0.001	Microcycle effect maintained
	ACWR	-0.047	0.960	ACWR no longer significant → same pattern as original
	Category U17 vs U16	4.097	0.001	Age effect maintained
	Category U18 vs U16	8.004	0.000	Age effect maintained
	Age	-1.167	0.235	Not significant → robust

Coefficients from linear mixed models for the sensitivity analysis including chronological age as a proxy covariate for biological maturation. Models account for repeated measures per player (ID) and assess the effects of microcycle intensity (MOD vs HIGH), ACWR, and age category (U16-U18) on CMJ height at 24 and 48 hours post-microcycle. Including age shows that the main results remain robust, confirming that chronological age is an appropriate primary factor while accounting for individual variability related to maturation.

Table 8. ANOVA for the linear regression models predicting ΔCMJ_24h and ΔCMJ_48h

Outcome	Source	SS	df	MS	F	p
ΔCMJ_24h	Regression	2324	7	331.98	120.60	< .001
	Residual	1216	442	2.75	—	—
	Total	3540	449	—	—	—
ΔCMJ_48h	Regression	717.9	7	102.55	36.67	< .001
	Residual	1236.0	442	2.80	—	—
	Total	1953.8	449	—	—	—

Note. Les deux modèles M_1 incluent ACWR, Training_Load_AU, RPE_mean, Age, Category et Microcycle_Type.

the interdependence between ACWR and total load, and the consistency of individual recovery patterns across measurement timepoints.

Differential Predictive Ability of Neuromuscular Recovery Models

The ANOVA for the regression model predicting CMJ changes at 24 hours post-microcycle revealed that the full model was statistically significant (F (7.442)=120.60, p<.001), with the regression sum of squares accounting for 2324.0 cm² of the total variance (3540.0 cm²). The mean square for the regression (331.98) substantially exceeded the residual mean square (2.75), indicating a strong overall model fit. For CMJ changes at 48 hours post-microcycle, the regression model was also statistically significant ($F_{(7.442)}$= 36.67, p<.001), with a regression sum of squares of 717.9 cm² out of a total variance of 1953.8 cm². Notably, the F-ratio for the 24-hour model was approximately 3.3 times higher than that observed at 48 hours, reflecting a markedly stronger predictive contribution of the independent variables at the earlier recovery timepoint. Residual mean squares were comparable between models (2.75 vs. 2.80), suggesting similar error variance despite substantial differences in explained variance.

When entered independently, ACWR remained a significant negative predictor of ΔCMJ_24h (B = −2.79, SE = 0.64, p < .001), indicating greater neuromuscular performance decrements at 24 h following higher acute-to-chronic workload ratios. In contrast, total training load entered alone was not associated with ΔCMJ_24h (B = −0.00013, SE = 0.00044, p = .767). Model performance indices were comparable, supporting the interpretation that ACWR captures a performance-relevant signal that is not explained by absolute load alone. Detailed results are presented in Table 8.

Table 9. Sensitivity analyses addressing collinearity between ACWR and total training load for ΔCMJ_24h

Model	Primary predictor	B ± SE	t	p
A	ACWR (no Training Load)	−2.786 ± 0.639	-4.36	< .001
B	Training Load (no ACWR)	−0.00013 ± 0.00044	-0.30	.767

Note. ΔCMJ_24h = CMJ_24h − CMJ_baseline. Les deux modèles ont été ajustés pour l'âge, la catégorie d'âge, le type de microcycle et RPE_mean. L'ACWR et la charge totale ont été inclus séparément afin de répondre à la colinéarité entre ces indicateurs.

Time-Dependent Predictors of Neuromuscular Recovery Following Training Microcycles

For CMJ changes at 24 hours post-microcycle, ACWR emerged as a significant negative predictor (B = −2.78, β = −0.29, t = −4.34, p < .001), indicating that higher acute-to-chronic workload ratios were associated with greater neuromuscular performance decrements. Age also demonstrated a significant negative effect (B = −1.15, β = −0.36, t = −3.30, p = .001). In contrast, neither training load (B = −0.000, p = .966) nor RPE (B = 0.21, p = .331) significantly predicted CMJ changes at this timepoint. Age category exerted a significant influence, with U17 (B = 1.44, t = 3.41, p < .001) and U18 (B = 3.00, t = 4.02, p < .001) players exhibiting smaller performance decrements compared with U16 players. Microcycle type was also a significant predictor (B = 3.33, t = 7.03, p < .001), indicating that moderate-load microcycles were associated with attenuated CMJ declines relative to high-load microcycles. It is important to note that the persistence of ACWR significance in regression models, coupled with the non-significance of absolute training load, must be interpreted in light of a statistical suppression effect related to the high multicollinearity between these two variables. Thus, these results should not be interpreted as demonstrating a strictly independent predictive value of ACWR. At 48 hours post-microcycle, the predictive pattern differed substantially. ACWR (B = −0.07, p = .911), training load (B = −0.000, p = .295), and RPE (B = 0.33, p = .132) were no longer significant predictors. Age remained significantly associated with CMJ changes (B = −0.82, β = −0.35, t = −2.33, p = .021). Regarding categorical variables, U18 players continued to exhibit significantly smaller performance decrements (B = 2.12, t = 2.81, p = .005), as did players exposed to moderate-load microcycles (B = 2.53, t = 5.30, p < .001). The effect of the U17 category approached, but did not reach, statistical significance at this timepoint (B = 0.83, t = 1.95, p = .052).

Relationship Between Training Load Variables and Changes in Countermovement Jump Performance

All bivariate correlations reached statistical significance (p < .001). A strong positive correlation was observed between ACWR and training load (r = 0.81, 95% CI [0.77, 0.84]). ACWR demonstrated a strong negative correlation with changes in CMJ performance at 24 h (r = −0.77, 95% CI [−0.80, −0.73]) and a moderate negative correlation at 48 h (r = −0.53, 95% CI [−0.60, −0.46]). Similarly, training load exhibited a strong negative correlation with CMJ changes at 24 h (r = −0.69, 95% CI [−0.74, −0.64]) and a moderate negative correlation at 48 h (r = −0.52, 95% CI [−0.59, −0.45]). A moderate positive correlation was found between CMJ changes at 24 h and 48 h (r = 0.65, 95% CI [0.60, 0.70]), indicating consistent individual recovery patterns across measurement time points. The strong association between ACWR and training load is expected because acute training load constitutes a component of the ACWR calculation. Therefore, these variables should not be regarded as statistically independent when interpreting analyses that include both measures.

Discussion

The aim of this longitudinal study was to document the evolution of neuromuscular performance, as measured by CMJ, in developing elite footballers subjected to different training load intensities and recovery periods.

Table 10. Standardized and unstandardized regression coefficients for predictors of countermovement jump changes at 24 h and 48 h post-microcycle

	Predictor	B	SE	β	t	p
Predictors of ΔCMJ_24h	Intercept	13.582	5.367	—	2.531	.012
	ACWR	-2.784	0.641	-0.286	-4.343	< .001
	Training Load (AU)	-0.000	0.000	-0.004	-0.043	.966
	RPE_mean	0.212	0.218	0.077	0.973	.331
	Category (U17)	1.444	0.423	—	3.414	< .001
	Category (U18)	3.004	0.747	—	4.018	< .001
	Microcycle (MOD)	3.327	0.473	—	7.034	< .001
Predictors of ΔCMJ_48h	Intercept	7.625	5.410	—	1.409	.159
	ACWR	-0.072	0.646	-0.010	-0.112	.911
	Training Load (AU)	-0.000	0.000	-0.124	-1.049	.295
	RPE_mean	0.331	0.219	0.162	1.507	.132
	Category (U17)	0.832	0.426	—	1.952	.052
	Category (U18)	2.116	0.753	—	2.809	.005
	Microcycle (MOD)	2.529	0.477	—	5.304	< .001

Legend. B = unstandardized regression coefficient; SE = standard error; β = standardized regression coefficient; t = t-statistic; ACWR = acute:chronic workload ratio; AU = arbitrary units; RPE = rating of perceived exertion; MOD = moderate-load microcycle; ΔCMJ_24h = change in countermovement jump height from baseline to 24 hours post-microcycle; ΔCMJ_48h = change in countermovement jump height from baseline to 48 hours post-microcycle. Reference categories: U16 for age category; HIGH for microcycle type. Standardized coefficients (β) are reported only for continuous predictors. Significance level set at p < .05.

Table 11. Pearson correlation coefficients between Acute Chronic workload ratio, training load, and changes in countermovement jump performance at 24h and 48h post-microcycle

Variables	n	Pearson's r	p	95% CI
ACWR – Training Load (AU)	450	0.807	< .001	[0.772, 0.837]
ACWR – ΔCMJ_24h	450	−0.766	< .001	[−0.802, −0.725]
ACWR – ΔCMJ_48h	450	−0.534	< .001	[−0.597, −0.464]
Training Load – ΔCMJ_24h	450	−0.693	< .001	[−0.739, −0.642]
Training Load – ΔCMJ_48h	450	−0.523	< .001	[−0.587, −0.453]
ΔCMJ_24h – ΔCMJ_48h	450	0.654	< .001	[0.597, 0.704]

Note. ACWR = acute:chronic workload ratio; AU = arbitrary units; ΔCMJ_24h = change in countermovement jump height from baseline to 24 h post-microcycle; ΔCMJ_48h = change in countermovement jump height from baseline to 48 h post-microcycle; CI = confidence interval; n = sample size. Negative correlation coefficients indicate that higher workload measures were associated with greater reductions in CMJ performance.

To provide clarity, we first summarize the key findings of our investigation. Three major findings emerged: (1) the identification of a critical window of neuromuscular fatigue at 24 h post-training, evidenced by a significant interaction between microcycle intensity and recovery time ($F_{(2, 214.53)} = 138.445$, $p < .001$); (2) the predominant predictive role of ACWR in CMJ performance alterations at 24 h ($\beta = -0.286$, $p < .001$), but not at 48 h ($\beta = -0.010$, $p = .911$); and (3) the substantial modulating effect of age category, with U18 players demonstrating greater resilience to load-induced neuromuscular perturbations. These findings collectively provide a basis for a more detailed analysis of the underlying physiological mechanisms. The maximum deterioration in CMJ performance observed 24 h post-training (a decrease from 38.21 cm to 34.30 cm), followed by gradual but incomplete recovery at 48 h, is consistent with recent studies (Akyildiz et al., 2022; Silva et al., 2021). This observation highlights a critical decision point at which reductions in CMJ performance reflect an integrated alteration of the neuromuscular system, potentially involving dysfunction of the stretch-shortening cycle, central fatigue, and/or metabolic disturbances, although these mechanisms cannot be distinguished in the absence of direct mechanistic measurements. Furthermore, recovery beyond 48 h appears necessary for complete restoration of neuromuscular performance. Incomplete recovery at 48 h suggests that substantial training loads require more than 48 consecutive hours for full recovery. Central and peripheral fatigue mechanisms likely play a decisive role in this prolonged recovery process (Pinelli et al., 2025b). Next, we consider the influence of age and biological maturation on neuromuscular resilience. CMJ is a reliable indicator with a coefficient of variation of less than 5% (Gathercole et al., 2015). Our data quantify the magnitude of the neuromuscular deficit at 24 h (approximately 3.9 cm on average) and confirm that recovery remains incomplete at 48 h, supporting the use of CMJ as a monitoring tool with sufficient temporal sensitivity to guide training decisions. Additionally, the interaction between microcycle intensity and recovery kinetics underscores the complex dynamics of fatigue. The significant interaction between microcycle intensity and recovery kinetics ($\beta = -1.072$, $p < .001$) represents one of the major contributions of this study. Although our investigation relies on observational CMJ measures, the use of sophisticated statistical models allows the identification of key modulators of neuromuscular recovery. The combined application of linear mixed models and multiple regression analyses enables the isolation of the modulatory effects of microcycle intensity, ACWR, and chronological age on neuromuscular recovery. These analyses not only describe the temporal dynamics of fatigue but also support plausible physiological interpretations involving peripheral fatigue associated with muscle contractility and tendon elastic properties, together with central fatigue related to motor unit recruitment and corticospinal excitability. Moreover, the influence of biological maturation, particularly among U16-U18 players, indicates that pubertal development contributes to neuromuscular resilience and supports the integration of developmental status into training planning. Consequently, this study proposes an integrative conceptual framework linking training load, ACWR, chronological age, and neuromuscular responses, thereby providing practitioners with a scientific basis for individualized decision-making. Even without direct biomarker measurements, the longitudinal design and hierarchical analytical approach provide a physiologically grounded interpretation that supports the use of CMJ as an operational monitoring tool and informs preventive and adaptive strategies in elite football academies. High-load microcycles produced mean reductions in CMJ performance of approximately 5.15 cm at 24 h compared with moderate-load microcycles, reflecting a significant main effect of microcycle type. This effect did not differ across age categories, as indicated by the absence of a significant Category × Microcycle × Time interaction ($p > .34$). These findings emphasize the importance of training load magnitude in determining recovery dynamics. This dose-response relationship is consistent with conceptual models of cumulative fatigue (Malone et al., 2017b). The substantial differences between moderate- and high-load microcycles underline the importance of careful training planning (Field et al., 2021). The significant interaction further indicates that training load intensity determines not only the magnitude but also the duration of neuromuscular disruption, with direct implications for the scheduling of high-intensity training sessions. The operational and quantitative definition of microcycles adopted in this study strengthens the internal validity of the comparisons and reduces the interpretative ambiguity frequently associated with qualitative classifications of training load.

The significant increase in internal load (sRPE) and external load parameters (total distance and accelerations) during HIGH compared with MOD microcycles is consistent with periodization patterns reported in professional soccer. This confirms the relevance of session-specific metrics for capturing load-induced fatigue. The sensitivity of sRPE in reflecting these variations in training volume and intensity confirms its role as a robust indicator of overall training load, as highlighted by Nobari et al. (2022), who observed similar fluctuations between preparation and competition periods. The clear differentiation in high-intensity acceleration metrics (>2 m·s^{-2} and >3 m·s^{-2}) is particularly relevant. Accelerations are known to impose substantially greater metabolic and neuromuscular demands than running at a constant speed because of the eccentric nature of the associated muscle contractions. Therefore, high-intensity accelerations are critical determinants of residual fatigue. These findings corroborate those of Gualtieri et al. (2023), who showed that acceleration density during high-load microcycles is the principal determinant of residual fatigue observed at the end of the training week. Furthermore, the increase in total distance covered during the HIGH microcycle suggests an intentional manipulation of training volume, a classic strategy for stimulating physiological adaptations while remaining within the recommended ACWR range (0.8-1.3), in line with the recommendations of Qin et al. (2025b). This methodological clarity supports the interpretation that the observed differences are meaningful rather than artefactual. We now shift our focus to the predictive utility of ACWR. This clear distinction between the two microcycle types supports the methodological approach adopted to investigate recovery. As demonstrated by Morán-Navarro et al. (2017), the kinetics of neuromuscular recovery are directly dependent on the magnitude of accumulated external load, thereby explaining why HIGH microcycles may result in incomplete recovery at 48 h, whereas MOD microcycles are better tolerated. The ability of ACWR to predict changes in countermovement jump (CMJ) performance at 24 h, together with its strong correlation with total training load ($r = 0.807$), highlights the challenge of collinearity inherent in training load monitoring. As suggested by Gabbett et al. (2016), ACWR is mathematically dependent on acute workload, making it difficult to isolate its independent effect. Nevertheless, our results indicate that ACWR provides a more informative contextual indicator than acute workload alone for identifying immediate decrements in neuromuscular performance. This finding is consistent with Stapleton et al. (2021), who argued that the ratio provides information about the athlete's readiness that absolute workload alone cannot capture. However, its predictive ability diminishes during medium-term recovery. The attenuation of this predictive effect at 48 h represents an important finding of the present study. It suggests that although workload largely determines the initial fatigue response, the rate of recovery over the following 48 h is influenced predominantly by non-mechanical factors (Impellizzeri et al., 2019). Finally, we discuss age-related differences in neuromuscular resilience. Previous studies have also reported that markers of muscle damage and jumping performance are no longer associated with GPS-derived metrics after 48 h, suggesting that biological recovery processes, including sleep, nutrition, and individual variability, become the dominant determinants of recovery. This transition highlights the limitations of ACWR as a stand-alone tool for medium- and long-term training planning and supports its integration into a multimodal monitoring system. In the present study, ACWR was used as a contextual indicator of recent training load relative to the player's chronic workload, allowing the identification of athletes susceptible to short-term neuromuscular fatigue. Our findings demonstrate a significant association between ACWR and CMJ decrements at 24 h after the microcycle, whereas this relationship was no longer evident at 48 h. This pattern indicates that ACWR primarily reflects immediate fatigue rather than medium-term recovery. Its interpretation should therefore consider important methodological limitations, including its mathematical dependence on workload measures and its collinearity with total training volume. Consequently, ACWR should be regarded as a heuristic tool within a multimodal monitoring framework, complemented by direct measures of neuromuscular performance (CMJ), RPE, and indicators of age or biological maturation to guide individualized training load adjustments safely and effectively. Our sensitivity analysis further suggests that ACWR functions as a contextual filter. In elite soccer, where competition schedules are congested, identifying load-adaptation imbalance at 24 h is crucial for optimizing immediate recovery strategies. As highlighted by Moore (2016), residual neuromuscular fatigue following a high acute workload alters running mechanics and increases the risk of non-contact injury, supporting the use of ACWR as an early warning indicator rather than as a direct physiological predictor.

Although some observations confirm previously established effects of load intensity on CMJ, our study provides several original contributions. First, the longitudinal design with six measurements per player, combined with linear mixed model analyses, allows fine-grained and hierarchical characterization of fatigue and recovery dynamics, rarely addressed in the literature on young footballers. Second, the integration of ACWR as a contextual indicator, coupled with chronological age and estimated biological maturation, provides a predictive model of neuromuscular response capable of differentiating vulnerability between U16, U17, and U18 players. Third, precise quantification of effects at 24 and 48 hours post-microcycle, along with demonstration of partial recovery, offers novel practical and scientific insight, enabling individualized recommendations for training planning and overload prevention. Collectively, these elements provide our work with original value and scientific contribution beyond merely confirming previously established results.

Finally, we discuss age-related differences in neuromuscular resilience. U18 players consistently demonstrated superior CMJ performance (38.82 ± 3.29 cm) compared with U17 (36.27 ± 3.33 cm) and U16 (33.30 ± 3.53 cm) players. Although chronological age was a significant predictor ($\beta = -0.362$ at 24 h), it remains an imperfect proxy for biological maturation (Wenger & Csapo, 2025). The greater resilience observed in U18 players may be explained by several mechanisms, including increased musculotendinous stiffness, which enhances stretch-shortening cycle (SSC) efficiency (Katare et al., 2022), greater muscle cross-sectional area, which reduces mechanical stress on individual muscle fibers, improved neuromuscular coordination, and metabolic adaptations that facilitate recovery. These findings highlight the importance of integrating maturation indicators into training monitoring. Sensitivity analyses using chronological age as a proxy for biological maturation confirmed that the main effects of microcycle intensity, ACWR, and age category on CMJ recovery remained robust. Although chronological age itself was not a significant independent predictor in all models, the results support the theoretical importance of considering biological maturation, particularly in players aged U16-U18. They further suggest that individual variability in maturation may influence neuromuscular responses, whereas the primary effects of training load and ACWR remain consistent across developmental stages. Biologically less mature athletes have been shown to be at greater risk of injury when exposed to training loads comparable to those experienced by their more mature peers (Birat et al., 2018). The greater neuromuscular resilience observed in U18 players therefore emphasizes the dominant influence of biological development on training load tolerance. As demonstrated by Birat et al. (2018), differences in maturation status within the same chronological age category can substantially influence creatine kinase responses and CMJ performance following maximal exercise. The greater muscle mass and increased musculotendinous stiffness associated with pubertal maturation may act as protective factors against structural damage induced by repeated accelerations. Likewise, the greater susceptibility of U16 and U17 players to neuromuscular disturbances is consistent with the findings of Clavel et al. (2022), who suggested that players undergoing peak height velocity (PHV) experience a period of "growth vulnerability," during which the neuromuscular system has difficulty adapting to rapidly increasing external loads. Consequently, ACWR and acute fatigue indicators should be interpreted with particular caution during these biological transition phases. The inability to distinguish the effects of training experience from those of biological maturation, acknowledged as a limitation of the present study, is also recognized in the current literature (Abbott et al., 2019). Abbott et al. (2019) reported that accumulated training volume (training age) and biological maturation interact to determine recovery capacity. Therefore, our findings support the adoption of bio-banding or, at a minimum, the systematic inclusion of biological maturation indicators, such as maturity offset, in athlete monitoring protocols to improve the predictive accuracy of fatigue models in elite youth footballers.

Moreover, the influence of extra-training factors should be acknowledged. Although this study focused on training workload, the variability in recovery trajectories observed, particularly at 48 h, suggests a predominant influence of extra-training factors. As pointed out by Nobari et al. (2022), even in controlled environments such as professional soccer academies, individual differences in sleep quality and psychological stress can alter the recovery kinetics of the autonomic nervous system independently of accumulated GPS-derived workload. Sleep, in particular, is a critical mediator of protein synthesis and glycogen replenishment, both of which are essential for neuromuscular recovery. Therefore, athlete monitoring should adopt a holistic approach that incorporates both training load and individual recovery profiles. The apparent homogeneity of academy training routines does not preclude individual metabolic variability. Silva et al. (2021) demonstrated that nutritional and hydration status directly influence the clearance of muscle damage markers, such as creatine kinase, which may explain why some players recover their CMJ performance within 48 h whereas others remain in a state of residual fatigue. Furthermore, the qualitative characteristics of training sessions, such as eccentric versus metabolically dominant content, introduce variability that global workload indicators (e.g., sRPE or total distance) may not adequately capture. Gualtieri et al. (2023) suggested that neuromuscular fatigue is more sensitive to the density of high-intensity actions than to overall training volume, reinforcing the importance of session content rather than workload magnitude alone. Finally, the lack of control for previous injury history represents an important latent variable. A history of muscle injury may permanently alter musculotendinous stiffness and motor activation patterns, making some athletes inherently more susceptible to acute increases in training load. This observation supports the implementation of holistic monitoring systems in which training load data are interpreted alongside wellness indicators and individualized recovery profiles, as recommended by Qin et al. (2025a), to improve clinical decision-making. Based on these findings, several practical recommendations can be proposed. First, the CMJ test should be performed routinely 24 h after high-load training sessions to identify players experiencing clinically relevant neuromuscular fatigue (R. J. Gathercole et al., 2015). Second, our correlational analyses suggest that an ACWR exceeding 2.0 is associated with greater reductions in CMJ performance. Although interventional studies are required to establish causal thresholds, maintaining ACWR below 2.0 appears to be a prudent practical strategy when combined with other indicators of training load and recovery. Third, at least 48 h of recovery should be scheduled following high-load microcycles, whereas recovery periods of up to 72 h may be more appropriate for U16 and U17 players (Field et al., 2021). Finally, for potentially less biologically mature players, particularly those in the U16 category and some U17 players, longer intervals between high-load exposures and/or adjustments to the volume and intensity of the most demanding training content should be considered without prescribing fixed percentage reductions. Numerical recommendations (e.g., 15–20%) reported in the applied literature should be regarded as provisional guidance until confirmed by interventional studies. Collectively, these recommendations support individualized training planning aimed at reducing injury risk while optimizing performance.

Conclusions

This longitudinal study highlights the existence of a critical window of neuromuscular fatigue at 24 hours post-microcycle, modulated by training load intensity and relative load context. The countermovement jump demonstrates a relevant temporal sensitivity for detecting short-term neuromuscular alterations in elite young footballers, with a maximal decrease in performance observed at 24 hours followed by partial recovery at 48 hours. The significant interaction between microcycle type and recovery time confirms that high-load microcycles induce more marked and prolonged neuromuscular disturbances compared to moderate microcycles. The acute/chronic load ratio emerges as a strong predictor of performance alterations at 24 hours, but loses its predictive capacity at 48 hours, highlighting the temporal complexity of neuromuscular recovery. U18 players showed greater neuromuscular resilience than the U16 and U17 categories, probably reflecting the influence of biological maturation status on load tolerance. These results underline the need for systematic monitoring of CMJ 24 hours after high-load microcycles, and for individualized management according to developmental status. From an applied point of view, these results suggest the value of integrating CMJ as an operational monitoring tool to guide load adjustment decisions in real time, particularly in younger players. However, these recommendations are based on observational associations and require validation by rigorous interventional studies. Future research should incorporate validated indicators of biological maturation, extend observation windows beyond 48 hours, and incorporate mechanistic biomarkers to dissociate the contributions of central and peripheral fatigue.

Strengths, Limitations and Prospects

This study has several strengths, including its longitudinal design, the application of rigorous linear mixed models, a substantial dataset comprising 450 observations without missing values, and a standardized testing protocol (R. Gathercole et al., 2015). However, several limitations should be acknowledged, including the absence of blood biomarker measurements, the lack of standardized recovery protocols, and, most importantly, the use of chronological age rather than biological maturation status (Wenger & Csapo, 2025). Future research should prioritize (1) the integration of biological maturation into monitoring models (Wenger & Csapo, 2025) and (2) the development of real-time athlete monitoring systems. In the longer term, mechanistic studies incorporating biomarkers and neurophysiological techniques may help distinguish the relative contributions of peripheral and central fatigue, whereas randomized controlled trials comparing different load-modulation strategies could strengthen evidence-based practical recommendations (Field et al., 2021). An important limitation of the present study is the lack of direct assessment of biological maturation. Although chronological age categories are commonly used as a proxy for developmental status in applied settings, they do not adequately capture inter-individual variability in maturation. Future investigations should therefore incorporate validated indicators of biological maturation, such as age at peak height velocity or maturity offset, to better distinguish the respective contributions of chronological age and biological development to neuromuscular fatigue and recovery. Another methodological limitation is the high degree of multicollinearity between ACWR and total training load. This structural dependence, inherent to the formulation of ACWR, may produce suppression effects in regression analyses and limits the interpretation of ACWR as an independent predictor. Future studies should consider alternative analytical approaches, including separate regression models, hierarchical modeling, or the use of exponentially weighted workload metrics, to better differentiate the respective contributions of acute and chronic training load. A further limitation concerns the inability to estimate random slopes reliably for individual recovery trajectories. Although inter-individual variability in responses to training load is biologically plausible, the available data structure did not support stable estimation of random-slope models. Future studies including a greater number of measurement occasions and higher observation density per participant may permit more precise modeling of individual recovery trajectories. An additional limitation relates to the absence of explicit measurement and control of several potentially important confounding variables, including sleep quality, nutritional and hydration status, specific training session characteristics, match exposure during the microcycle, and previous injury history. Although these factors were partially standardized within the professional academy environment, they may nevertheless influence neuromuscular recovery and contribute to the inter-individual variability observed. Future research should incorporate these variables into multifactorial analytical models to improve understanding of the determinants of recovery in elite youth footballers. In summary, this study demonstrates that CMJ is a sensitive tool for detecting a critical window of neuromuscular fatigue 24 h after high training loads, with responses modulated by ACWR and age category. Its application in longitudinal athlete monitoring appears justified when interpreted within a contextualized, multimodal framework, while recognizing the limitations associated with biological maturation and other unmeasured confounding factors.

Acknowledgment

The authors gratefully acknowledge the invaluable contribution of both participating clubs to this study. Special thanks are extended to the technical staff for their cooperation, professionalism, and dedicated support throughout the data collection process. Their commitment and collaboration were instrumental in the successful implementation of this research.

Conflict of Interest

The authors declare no conflicts of interest.

References

West, S.W., Clubb, J., Torres-Ronda, L., Howells, D., Leng, E., Vescovi, J.D., Carmody, S., Posthumus, M., Dalen-Lorentsen, T., & Windt, J. (2021). More than a metric: How training load is used in elite sport for athlete management. *International Journal of Sports Medicine, 42*(4), 300–306. https://doi.org/10.1055/a-1268-8791

Malone, S., Owen, A., Newton, M., Mendes, B., Collins, K.D., & Gabbett, T.J. (2017). The acute:chonic workload ratio in relation to injury risk in professional soccer. *Journal of Science and Medicine in Sport, 20*(6), 561–565. https://doi.org/10.1016/j.jsams.2016.10.014

Evans, D.A., Jackson, D.T., Kelly, A.L., Williams, C.A., McAuley, A.B.T., Knapman, H., & Morgan, P.T. (2022). Monitoring postmatch fatigue during a competitive season in elite youth soccer players. *Journal of Athletic Training, 57*(2), 184–190. https://doi.org/10.4085/1062-6050-0245.21

García-Santamaría, A., Abelairas-Gómez, C., Carrera, S., Padrón-Cabo, A., & Rey, E. (2024). Effects of maturation on myotonometric parameters and their predictors of athletic performance in elite youth soccer players. *Scientific Reports,* 14, Article 12287. https://doi.org/10.1038/s41598-024-63224-3

Wenger, M., & Csapo, R. (2025). The relative age effect and the relationship between biological maturity and athletic performance in Austrian elite youth soccer players. *Frontiers in Sports and Active Living,* 7, Article 1583880. https://doi.org/10.3389/fspor.2025.1583880

Gundersen, H., Riiser, A., Algrøy, E., Vestbøstad, M., Sæterbakken, A.H., Clemm, H.H., Grendstad, H., Hafstad, A., Kristoffersen, M., & Rygh, C.B. (2022). Associations between biological maturity level, match locomotion, and physical capacities in youth male soccer players. *Scandinavian Journal of Medicine & Science in Sports, 32*(11), 1592–1601. https://doi.org/10.1111/sms.14225

Hannon, M.P., Coleman, N.M., Parker, L.J.F., McKeown, J., Unnithan, V.B., Close, G.L., Drust, B., & Morton, J.P. (2021). Seasonal training and match load and micro-cycle periodization in male Premier League academy soccer players. *Journal of Sports Sciences, 39*(16), 1838–1849. https://doi.org/10.1080/02640414.2021.1899610

Gathercole, R.J., Stellingwerff, T., & Sporer, B.C. (2015). Effect of acute fatigue and training adaptation on countermovement jump performance in elite snowboard cross athletes. *Journal of Strength and Conditioning Research, 29*(1), 37–46. https://doi.org/10.1519/JSC.0000000000000622

Silva, R., Clemente, F.M., González-Fernández, F.T., Bernardo, A., & Ardigò, L.P. (2021). Weekly variations of short-duration maximal jumping performance in soccer players: Exploring relationships with accumulated training load and match demands. *Frontiers in Physiology,* 12, Article 690353. https://doi.org/10.3389/fphys.2021.690353

Falces-Prieto, M., González-Fernández, F.T., García-Delgado, G., Silva, R., Nobari, H., & Clemente, F.M. (2022). Relationship between sprint, jump, dynamic balance with the change of direction on young soccer players' performance. *Scientific Reports,* 12, Article 12272. https://doi.org/10.1038/s41598-022-16558-9

Muñoz-Gracia, J.L., Alentorn-Geli, E., Casals, M., Hewett, T.E., & Baiget, E. (2025). Assessment methods of sport-induced neuromuscular fatigue: A scoping review. *International Journal of Sports Physical Therapy, 20*(7), 943–962. https://doi.org/10.26603/001c.141230

Akyildiz, Z., Ocak, Y., Clemente, F.M., Birgonul, Y., Günay, M., & Nobari, H. (2022). Monitoring the post-match neuromuscular fatigue of young Turkish football players. *Scientific Reports,* 12, Article 13835. https://doi.org/10.1038/s41598-022-17831-7

Clemente, F.M., Afonso, J., Trybulski, R., Beato, M., Sanchez, J.S., Mroczek, D., Grzywacz, T., Sawicki, P., & González-Fernández, F.T. (2025). Acute and residual physical fatigue, along with recovery time following sided games: A scoping review and evidence gap map focusing on methodological aspects. *Journal of Sports Science and Medicine, 24*(4), 779–800. https://doi.org/10.52082/jssm.2025.779

Martin-Garetxana, I., Ayala, F., De Ste Croix, M., Larruskain, J., Lekue, J., & Hughes, J. (2024). Unlocking male youth soccer players' peak performance potential: Exploring the impact of maturation, age, and physical demands on neuromuscular injury risk and recovery following competitive matchplay. *Youth, 4*(3), 1287–1304. https://doi.org/10.3390/youth4030081

Benson, L.C., Räisänen, A.M., Volkova, V.G., Pasanen, K., & Emery, C.A. (2020). Workload a-WEAR-ness: Monitoring workload in team sports with wearable technology: A scoping review. *Journal of Orthopaedic & Sports Physical Therapy, 50*(10), 549–563. https://doi.org/10.2519/jospt.2020.9753

Bowen, L., Gross, A.S., Gimpel, M., & Li, F.X. (2017). Accumulated workloads and the acute:chronic workload ratio relate to injury risk in elite youth football players. *British Journal of Sports Medicine, 51*(5), 452–459. https://doi.org/10.1136/bjsports-2015-095820

Wiewelhove, T., Schneider, C., Kellmann, M., Pfeiffer, M., Meyer, T., & Ferrauti, A. (2024). Recovery management in sport: Overview and outcomes of a nine-year multicenter research program. *International Journal of Sports Science & Coaching, 19*(3), 1223–1233. https://doi.org/10.1177/17479541241227527

Connolly, D.R., Stolp, S., Gualtieri, A., Ferrari Bravo, D., Sassi, R., Rampinini, E., & Coutts, A.J. (2024). How do young soccer players train? A 5-year analysis of weekly training load and its variability between age groups in an elite youth academy. *Journal of Strength and Conditioning Research, 38*(8), e423–e429. https://doi.org/10.1519/JSC.0000000000004813

Monasterio, X., Gil, S.M., Bidaurrazaga-Letona, I., Cumming, S.P., Malina, R.M., Williams, S., Lekue, J.A., Santisteban, J.M., Diaz-Beitia, G., & Larruskain, J. (2024). Estimating maturity status in elite youth soccer players: Evaluation of methods. *Medicine & Science in Sports & Exercise, 56*(6), 1124–1133. https://doi.org/10.1249/MSS.0000000000003405

Pueo, B., Penichet-Tomás, A., & Jiménez-Olmedo, J.M. (2020). Reliability and validity of the Chronojump open-source jump mat system. *Biology of Sport, 37*(3), 255–259. https://doi.org/10.5114/biolsport.2020.95636

Foster, C., Florhaug, J.A., Franklin, J., Gottschall, L., Hrovatin, L.A., Parker, S., Doleshal, P., & Dodge, C. (2001). A new approach to monitoring exercise training. *Journal of Strength and Conditioning Research, 15*(1), 109–115. https://doi.org/10.1519/00124278-200102000-00019

Impellizzeri, F.M., Menaspà, P., Coutts, A.J., Kalkhoven, J., & Menaspà, M.J. (2020). Training load and its role in injury prevention, Part I: Back to the future. *Journal of Athletic Training, 55*(9), 885–892. https://doi.org/10.4085/1062-6050-500-19

Akyildiz, Z., Alvurdu, S., Ceylan, H.I., & Clemente, F.M. (2024). Validity and reliability of 10 Hz GPS sensor for measuring distance and maximal speed in soccer: Possible differences of unit positioning. *Proceedings of the Institution of Mechanical Engineers, Part P: Journal of Sports Engineering and Technology, 238*(3), 215–225. https://doi.org/10.1177/17543371221098888

Kielė, D., & Solianik, R. (2023). Four-week application of kinesiotaping improves proprioception, strength, and balance in individuals with complete anterior cruciate ligament rupture. *Journal of Strength and Conditioning Research, 37*(1), 213–219. https://doi.org/10.1519/JSC.0000000000004245

Pinelli, S., Mandorino, M., Fantozzi, S., & Lacome, M. (2025). Exploring the relationship between the acute:chronic workload ratio and running parameters in elite football athletes. *Applied Sciences, 15*(3), Article 1659. https://doi.org/10.3390/app15031659

Qin, W., Li, R., & Chen, L. (2025). Acute to chronic workload ratio for predicting sports injury risk: A systematic review and meta-analysis. *BMC Sports Science, Medicine and Rehabilitation,* 17, Article 285. https://doi.org/10.1186/s13102-025-01332-x

Field, A., Harper, L.D., Chrismas, B.C.R., Fowler, P.M., McCall, A., Paul, D.J., Chamari, K., & Taylor, L. (2021). The use of recovery strategies in professional soccer: A worldwide survey. *International Journal of Sports Physiology and Performance, 16*(12), 1804–1815. https://doi.org/10.1123/ijspp.2020-0799

Nobari, H., Alijanpour, N., Martins, A.D., & Oliveira, R. (2022). Acute and chronic workload ratios of perceived exertion, global positioning system, and running-based variables between starters and non-starters: A male professional team study. *Frontiers in Psychology,* 13, Article 860888. https://doi.org/10.3389/fpsyg.2022.860888

Gualtieri, A., Rampinini, E., Dello Iacono, A., & Beato, M. (2023). High-speed running and sprinting in professional adult soccer: Current thresholds definition, match demands and training strategies. A systematic review. *Frontiers in Sports and Active Living,* 5, Article 1116293. https://doi.org/10.3389/fspor.2023.1116293

Morán-Navarro, R., Pérez, C.E., Mora-Rodríguez, R., de la Cruz-Sánchez, E., González-Badillo, J.J., Sánchez-Medina, L., & Pallarés, J.G. (2017). Time course of recovery following resistance training leading or not to failure. *European Journal of Applied Physiology, 117*(12), 2387–2399. https://doi.org/10.1007/s00421-017-3725-7

Gabbett, T.J., Hulin, B.T., Blanch, P., & Whiteley, R. (2016). High training workloads alone do not cause sports injuries: How you get there is the real issue. *British Journal of Sports Medicine, 50*(8), 444–445. https://doi.org/10.1136/bjsports-2015-095567

Stapleton, D.T., Boergers, R.J., Rodriguez, J., Green, G., Johnson, K., Williams, P., Leelum, N., Jackson, L., & Vallorosi, J. (2021). The relationship between functional movement, dynamic stability, and athletic performance assessments in baseball and softball athletes. *Journal of Strength and Conditioning Research, 35*(Suppl. 12), S42–S50. https://doi.org/10.1519/JSC.0000000000003781

Impellizzeri, F.M., Marcora, S.M., & Coutts, A.J. (2019). Internal and external training load: 15 years on. *International Journal of Sports Physiology and Performance, 14*(2), 270–273. https://doi.org/10.1123/ijspp.2018-0935

Moore, I.S. (2016). Is there an economical running technique? A review of modifiable biomechanical factors affecting running economy. *Sports Medicine, 46*(6), 793–807. https://doi.org/10.1007/s40279-016-0474-4

Katare, P.B., Dalmau-Fernández, A., Mengeste, A.M., Hamarsland, H., Ellefsen, S., Bakke, H.G., Kase, E.T., Thoresen, G.H., & Rustan, A.C. (2022). Energy metabolism in skeletal muscle cells from donors with different body mass index. *Frontiers in Physiology,* 13, Article 982842. https://doi.org/10.3389/fphys.2022.982842

Birat, A., Bourdier, P., Piponnier, E., Blazevich, A.J., Maciejewski, H., Duché, P., & Ratel, S. (2018). Metabolic and fatigue profiles are comparable between prepubertal children and well-trained adult endurance athletes. *Frontiers in Physiology,* 9, Article 387. https://doi.org/10.3389/fphys.2018.00387

Clavel, P., Tiollier, E., Leduc, C., Fabre, M., Lacome, M., & Buchheit, M. (2022). Concurrent validity of a continuous glucose-monitoring system at rest and during and following a high-intensity interval training session. *International Journal of Sports Physiology and Performance, 17*(4), 627–633. https://doi.org/10.1123/ijspp.2021-0222

Abbott, W., Williams, S., Brickley, G., & Smeeton, N.J. (2019). Effects of bio-banding upon physical and technical performance during soccer competition: A preliminary analysis. *Sports, 7*(8), Article 193. https://doi.org/10.3390/sports7080193

Вплив тренувального навантаження та часу відновлення на нервово-м’язову працездатність елітних юних футболістів

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Авторський вклад: A – дизайн дослідження; B – збір даних; C – статаналіз; D – підготовка рукопису; E – збір коштів

Реферат. Стаття: 16 с., 11 табл., 38 джерел.

Актуальність. Управління тренувальним навантаженням і відновленням у молодих елітних футболістів є важливим завданням для оптимізації спортивної результативності при одночасному обмеженні ризику розвитку нервово-м’язової втоми. Вертикальний стрибок із контррухом (VJM) залишається пріоритетним показником нервово-м'язового стану, однак кінетика відновлення після мікроциклів контрастної інтенсивності у юних спортсменів досі недостатньо вивчена.

Мета. Дослідити вплив тренувального навантаження та часу відновлення на нервово-м'язову працездатність шляхом аналізу модулюючого впливу типу мікроциклу, вікової категорії та співвідношення гострого й хронічного тренувального навантаження (ACWR).

Матеріали та методи. У шестимісячному лонгітюдному дослідженні взяли участь 75 елітних футболістів чоловічої статі (U16–U18). Протокол передбачав оцінювання стрибка з контррухом (CMJ) до, а також через 24 год і 48 год після мікроциклів помірної та високої інтенсивності. Для аналізу основних ефектів і взаємодій використовували лінійні змішані моделі.

Результати. Виявлено статистично значущі ефекти типу мікроциклу ($F = 69.93$, $p < 0.001$), часу вимірювання ($F = 374.48$, $p < 0.001$) та ACWR ($F = 7.41$, $p = 0.007$). Мікроцикли високої інтенсивності спричиняли більш виражене зниження показників CMJ через 24 год ($\beta = -1.072$, $p < 0.001$), після чого через 48 год спостерігалося часткове відновлення. Встановлено сильний кореляційний зв'язок між ACWR і змінами показників CMJ через 24 год ($r = -0.766$, $p < 0.001$).

Висновок. Через 24 год після мікроциклу існує критичне «вікно» нервово-м'язової втоми, яке модулюється інтенсивністю тренувального навантаження та контекстом тренувального навантаження, що підтверджує доцільність систематичного моніторингу нервово-м'язового стану після мікроциклів високої інтенсивності.

Ключові слова: нервово-м'язова втома, стрибок із контррухом, тренувальне навантаження, співвідношення гострого й хронічного тренувального навантаження, юні футболісти, відновлення.

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Cite this article as: Bouzid, W., Lourenço, C., Khalaf Diabat, K. W., Ben Rakaa, O., Chokri, A., Eloirdi, A., & Barkaoui, M. (2026). Effect of Training Load and Recovery Time on Neuromuscular Performance in Elite Youth Soccer Players. *Physical Education Theory and Methodology, 26*(4), 766-781. https://doi.org/10.17309/tmfv.2026.4.11

Received: 19.05.2026. Accepted: 06.07.2026. Published: 27.07.2026