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Exploring the Relationship Between the Acute:Chronic Workload Ratio and Running Parameters in Elite Football Athletes

Salvatore Pinelli [1], Mauro Mandorino [2,3,*], Silvia Fantozzi [4] and Mathieu Lacome [2,5]

1 Department for Life Quality Studies, University of Bologna, Corso D'Augusto 237, 47921 Rimini, Italy; salvatore.pinelli2@unibo.it
2 Performance and Analytics Department, Parma Calcio 1913, 43124 Parma, Italy; mlacome@parmacalcio1913.com
3 Department of Movement, Human and Health Sciences, University of Rome "Foro Italico", 00135 Rome, Italy
4 Department of Electrical, Electronic, and Information Engineering "Guglielmo Marconi", University of Bologna, 40127 Bologna, Italy; silvia.fantozzi@unibo.it
5 Sport Expertise and Performance Laboratory, French National Institute of Sports (INSEP), 75012 Paris, France
* Correspondence: mmandorino@parmacalcio1913.com

Featured Application: This work investigates the relationship between the acute:chronic workload ratio (ACWR) and specific running parameters in elite football players.

Abstract: In contemporary sports science, the integration of wearable inertial measurement units (IMUs) has revolutionized athlete performance monitoring, offering insights into training load management and injury risk mitigation. The acute:chronic workload ratio (ACWR) has emerged as a pivotal metric, indicating the balance between acute training stress and chronic adaptation. This study investigates the relationship between ACWR and running parameters, i.e., contact time (CT), flight time (FT), and vertical stiffness (K_{vert}). Data from thirty-five elite male soccer players were analyzed using the WIMU Pro system. Statistical analyses showed that CT increased with workload, with significant differences observed between athletes in the sweet spot and others in the danger zone ($p < 0.05$), and effect sizes (Cohen's d) ranging from 0.28 to 0.37. K_{vert} values were consistently lower in athletes in the danger zone across all workload indicators ($p < 0.001$), with large effect sizes going up to 0.94. Conversely, FT showed no significant variation between ACWR groups. These findings suggest that elevated ACWRs may be linked to reductions in vertical stiffness, highlighting a potential increase in risk of injury. Coaches and practitioners can utilize these insights to tailor training programs, integrating load monitoring with tactical considerations to optimize athlete performance. Understanding the nuanced interplay between workload ratios and biomechanical parameters provides valuable insights for performance optimization for elite football athletes.

Keywords: ACWR; training load management; vertical stiffness; inertial measurement units; running test

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Academic Editor: Mark King

Received: 20 December 2024
Revised: 29 January 2025
Accepted: 5 February 2025
Published: 6 February 2025

Citation: Pinelli, S.; Mandorino, M.; Fantozzi, S.; Lacome, M. Exploring the Relationship Between the Acute:Chronic Workload Ratio and Running Parameters in Elite Football Athletes. *Appl. Sci.* **2025**, *15*, 1659. https://doi.org/10.3390/app15031659

1. Introduction

In contemporary sports science, the monitoring of athlete performance has been revolutionized by wearable technology, particularly through the use of inertial measurement units (IMUs). IMUs are wearable devices integrating accelerometers, gyroscopes, and magnetic sensors to measure motion-related parameters, such as angular velocity, linear acceleration, and orientation, through sensor fusion algorithms [1]. These devices provide a real-time, comprehensive view of training loads and physiological responses in ecological environments [2]. The use of IMUs, combined with other wearable sensors (e.g., Global Positioning System, GPS), is increasingly becoming a staple in athlete monitoring [3], particularly for elite team sports such as football, where maintaining peak performance and minimizing injuries is critical. These systems are highly scalable, making them effective tools for large teams and underscoring their importance in modern sports science. This capability has significantly enhanced the precision of training programs, helping coaches to better optimize performance and mitigate injury risks. These integrated devices are primarily used to quantify locomotor patterns, and the intensity achieved during training or matches. They provide numerous workload metrics, categorized into kinematic (movement at various running speeds), metabolic (estimated energy cost during activity) [4], and mechanical (load on the body during accelerations and decelerations) [5].

Central to modern training strategies is the concept of monitoring training loads to achieve an optimal balance between physical stress and recovery [6]. In this field, the acute:chronic workload ratio (ACWR), conceptualized by Gabbett [7], is frequently utilized to evaluate athlete readiness and injury susceptibility. This ratio, calculated as a fraction between the current week's training load (acute load) and a rolling average of the preceding four weeks (chronic load), offers insights into the balance between acute training stress and chronic training adaptation. Research has shown a strong correlation between heightened ACWRs and increased injury susceptibility in athletes [8–10]. Specifically, when the ACWR exceeded a value of 1.5, indicating a workload 1.5 times higher than the athlete's preparedness level, the risk of injury increased by two–four times in the following seven days [7,11]. Notwithstanding recent criticism, it remains a measure of interest within sports science. Some studies [12–14] acknowledge and support its application, suggesting that it may help guide training strategies. Research suggests that the ACWR can serve as a useful tool when incorporated into a multifaceted monitoring system alongside other established methods for managing load and injury risk [15]. Notably, while the ACWR shows an association with injury risk, it is not designed to function as a predictor of injury occurrence. It is important to emphasize that this association should not be mistaken for an ability to predict injuries at the individual player level [16,17].

Others, however, have questioned its methodological foundations and predictive value, emphasizing issues such as statistical artifacts, the lack of predictive accuracy, and unjustified reclassification caused by its ratio-based approach. Impellizzeri et al. [18,19] demonstrated that the ACWR magnifies the effect of acute workload (AL) without adding meaningful predictive value. Lolli et al. [20] and Curran-Everett [21] further criticized the use of ratios, highlighting their susceptibility to noise, spurious correlations, and inflated odds ratios.

To better understand how team sports athletes respond to training loads, the integration of IMUs with GPS sensors has become common practice, as this combination provides more comprehensive and detailed performance metrics. Among these metrics, vertical stiffness (K_{vert}) is a key biomechanical parameter reflecting the body's ability to store and release elastic energy during dynamic activities. Adequate vertical stiffness is associated with running efficiency [22], minimizing energy expenditure [23] while maximizing elastic energy return, which ultimately supports improved athletic performance [2,24–26]. Conversely, reduced stiffness can indicate fatigue, suboptimal running mechanics, or increased injury risk. In efficient running, short contact times and longer flight times are generally desirable, as they indicate effective force transfer and propulsion. High contact time generally reflects a less efficient stride cycle. As running intensity increases, flight time typically increases and contact time decrease, reflecting a more aerial gait pattern and leading to a higher level of generated power within each stride [27–29]. However, if a fatigue effect emerges—especially at higher intensities—contact time tends to increase, while flight time and stride frequency decrease, indicating altered neuromuscular control and reduced running efficiency. These changes can also coincide with larger joint angles, thereby impacting an athlete's ability to maintain optimal running mechanics [30]. These running parameters provide valuable insights into an athlete's running mechanics, efficiency, and potential fatigue levels. Monitoring vertical stiffness, flight and contact times across different intensities can help practitioners detect early signs of fatigue, minimize injury risk, and make data-driven adjustments in training load to preserve running form and performance. Athletes with sufficient vertical stiffness while running may accomplish running activities more efficiently (with fewer vertical COM displacements) and with higher performance by obtaining a higher potential elastic energy return from musculotendinous tissues [31].

This study aims to explore the relationship between ACWR and running parameters, including vertical stiffness (K_{vert}), CT and FT in elite football athletes. By investigating this relationship across various intrinsic parameters, including total distance (TD), running meters at different speeds (HS19 and HS25), and mechanical work (MW), our study aims to contribute novel insights into optimizing training strategies in team sports, providing insights into its role as a potential marker for monitoring workload and fatigue in elite athletes.

2. Materials and Methods

2.1. Study Design

This longitudinal observational study analyzed temporal parameters (K_{vert}, contact time [CT], and flight time [FT]) and training load variations (ACWRs) among elite male football players competing in the Italian second division (Serie B) throughout the 2022/23 season. Conducted at an Italian professional football club, the study involved first-team players, excluding those who participated in less than 60% of training sessions, to ensure consistent training data [32,33]. Data collection occurred during every training session, with analyses being performed on a weekly basis.

2.2. Participants

Thirty-five elite male players (age: 24 $\pm$ 5 years; weight: 80 $\pm$ 6.5 kg; height: 184.6 $\pm$ 5.4 cm) were included in the study. Prior to data collection, all participants were briefed on the study protocols, including the potential risks involved. This study includes human participants and was approved by the University of Bologna Bioethics Committee (protocol No. 0351259). In order to maintain the players' privacy, all data were anonymized before the analysis, in accordance with the principles of the Declaration of Helsinki.

2.3. Experimental Setup

All subjects performed a tempo box-to-box run, incorporated into the team's warm-up phase. Participants completed the test 40 times over the course of the season (40 weeks), with sessions conducted on the third day after a match (MD+3). The test consisted of four paced, high-speed runs. Each run was 60 m long, and the players had to complete the run in 12 s (average speed $\approx$ 18 km/h) with 33 s of recovery between trials, as suggested in previous research [34] (illustrated in Figure 1).

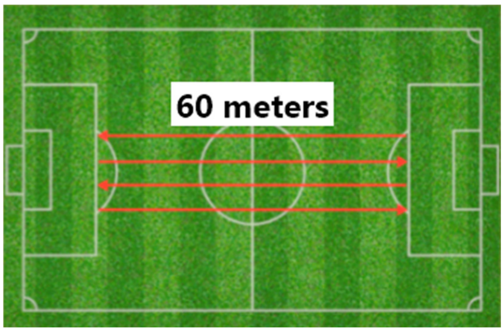

Figure 1. Description of the box-to-box run test.

2.4. Data Collection

Data were collected using the WIMU PRO™ device (RealtrackSystems S.L., Almeria, Spain), a wearable inertial measurement unit (IMU) widely used in sports science for monitoring physical activity and external load. The WIMU PRO™ integrates multiple sensors, including Global Positioning System (GPS) and Local Positioning System (LPS) technologies, allowing precise tracking of player movements during training and matches. The GPS and the LPS both function at a frequency of 18 Hz. The system also includes four 3D accelerometers (±16 g, ±32 g, and ±400 g) with sampling rates adjustable from 10 to 1000 Hz, three 3D gyroscopes (±500°/s, ±2000°/s, and ±4000°/s full-scale output range) operating at 1000 Hz, a 3D magnetometer, and a barometer. Validation studies have demonstrated the accuracy and reliability of this device for measuring various physical parameters [35–39]. The sensor was positioned between the players' scapulae using a specially designed tight vest to ensure stability and consistent data collection, as described in Figure 2.

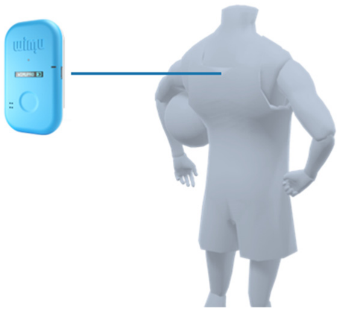

Figure 2. Sensor placement: WIMU PRO™ device positioned between the scapulae using a specific tight-fitting vest. Adapted from Pinelli et al. (2024) [39].

The inertial devices were synchronized and calibrated before use. The calibration procedure was carried out manually in accordance with the manufacturer's guidelines. Users were instructed to activate the device outdoors, ensuring minimal signal interference from nearby structures. Consistent with the recommendations of Maddison and Ni Mhurchu [40], all devices were activated 30 min before data collection to facilitate satellite signal acquisition and synchronize the GPS clock with the satellite's atomic clock [41]. Eighteen different parameters were extracted (Table 1).

The external load variables, such as total distance, high-speed running distances (>19.8 km/h and >25.2 km/h), and mechanical work, were derived from the GPS and IMU data. Mechanical work was defined as the cumulative sum of acceleration/deceleration events greater than 3.5 G. To mitigate drift in horizontal displacement, calibration protocols were regularly performed, and post-processing corrections were applied using the manufacturer's software.

Table 1. Extracted external load data and running parameters.

External Load Data	Acute:Chronic Workload Ratio, computed based on total distance (TD) [m], running meters at speeds > 19.8 km/h (HS19) [m], running meters at speeds > 25.2 km/h (HS25) [m], and mechanical work (MW)
Running Parameters	Average vertical stiffness (kN/m), average vertical stiffness z-score, average contact time (ms), average contact time z-score, average flight time (ms), average flight time z-score, and average speed (km/h)

The ACWR can be calculated using various window durations, with the 7:28-day ratio being the most common in soccer. This is because weekly fixtures justify a 7-day acute window [15,42]. Consequently, acute and chronic loads for the external load variables were determined using 7-day and 28-day rolling averages, respectively. The ACWR was categorized into three groups: underload (<0.8), sweet spot (0.8–1.5), and danger zone (>1.5) [7]. Running parameters were then assigned to these groups based on their ACWR values.

2.5. Statistical Analysis

A within-subject linear mixed model was employed to analyze the variation in running parameters in relation to the ACWR groups. The linear mixed model was chosen because it accounts for both fixed and random effects, allowing for variability within participants. Additionally, standardized effect sizes were computed. Effect size (ES) values of 0.2, 0.5, and 0.8 were considered to be small, moderate, and large differences, respectively [43]. The statistical analysis was performed in IMB SPSS Statistics version 25.0 (SPSS Inc., Chicago, IL, USA) for the Windows statistical software package. Results were deemed significant when $p < 0.05$.

3. Results

Table 2 illustrates the distribution of the running parameters across different ACWRs. CT generally increases as the workload progresses from underload to danger zone across all conditions. FT, instead, slightly decreases, increasing the load. K_{vert} shows a decrease in the danger zone compared to other conditions.

Table 2. Running parameters' distributions.

ACWR	Load Condition	Contact Time (ms)	Flight Time (ms)	Vertical Stiffness (kN/m)
Total Distance (TD)	Underload	212 ± 26	106 ± 25	59.8 ± 6.5
	Sweet spot	217 ± 26	95 ± 23	59.3 ± 6.5
	Danger zone	227 ± 27	95 ± 24	54.7 ± 6.4
Speed > 19.8 km/h (HS19)	Underload	209 ± 25	102 ± 23	60.5 ± 6.3
	Sweet spot	217 ± 26	94 ± 23	59.4 ± 6.5
	Danger zone	226 ± 26	95 ± 24	55.1 ± 6.2
Speed > 25.2 km/h (HS25)	Underload	219 ± 27	96 ± 24	58.1 ± 5.7
	Sweet spot	216 ± 26	95 ± 23	59.9 ± 6.8
	Danger zone	224 ± 26	94 ± 23	56.3 ± 6.9
Mechanical work (MW)	Underload	215 ± 26	97 ± 23	58.5 ± 4.6
	Sweet spot	217 ± 26	95 ± 23	59.5 ± 6.5
	Danger zone	212 ± 26	106 ± 25	59.8 ± 6.5

Kvert demonstrates statistically significant differences in distinguishing the danger zone group from the other two groups across all ACWR calculation methods, as shown in Table 3. In contrast, FT does not reveal significant differences between groups, as indicated in Table 4. CT differentiates athletes in the sweet spot from those in the danger zone under most ACWR methods; however, only the HS19 method identifies differences between underload and danger zone, as detailed in Table 5. The complete results, including all statistical comparisons across workload ratios, presented in Tables 3–5, support these observations: for CT, significant differences between athletes in the sweet spot and in the danger zone are noted in TD, HS19, and HS25 ACWRs, with effect sizes (Cohen's d) of 0.37, 0.33, and 0.28, respectively. For K_{vert}, significant differences are present between the danger zone and both other conditions across all parameters (TD, HS19, HS25, MW), with very strong effect sizes for TD (d = 0.91), HS19 (d = 0.81), and HS25 (d = 0.59), while FT remains unaffected across different conditions, as shown in Figure 3.

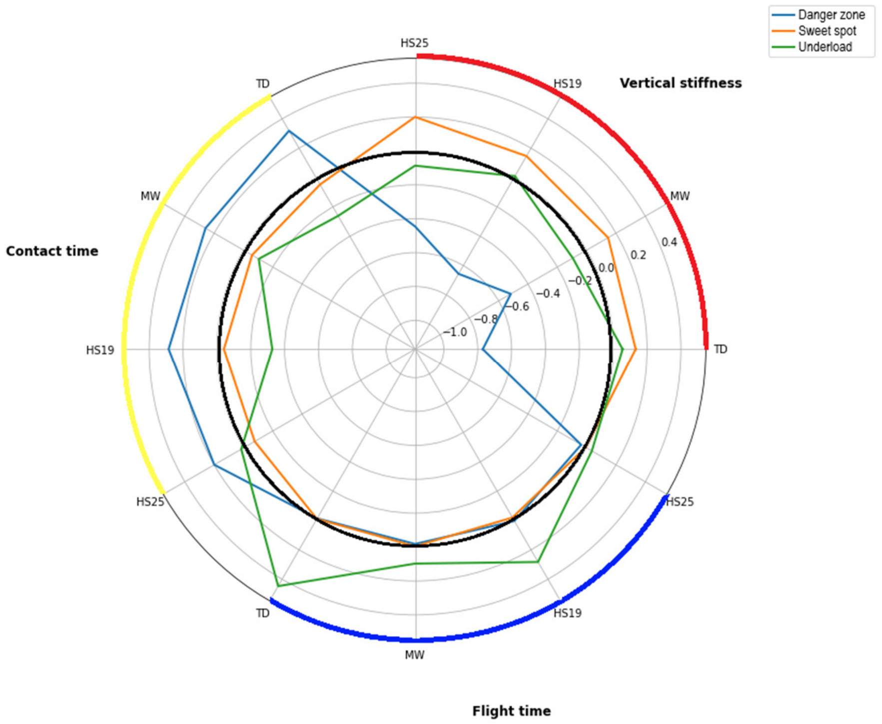

Figure 3. Radar chart of temporal parameters—CT, FT, and K_{vert}—across four ACWR conditions. Each color represents a loading condition: danger zone (blue), sweet spot (orange), and underload (green). The black line indicates a z-score equal to 0 as a baseline for comparison.

Table 3. Z-score test vertical stiffness.

ACWR	Comparison	Mean Difference	Standard Error	*p*-Value	Cohen's d
Total Distance (TD)	Underload vs. Sweet spot	−0.077	0.228	0.735	
	Underload vs. Danger zone	0.826 *	0.243	0.001 *	0.94
	Sweet spot vs. Danger zone	0.903 *	0.101	<0.001 *	0.91
Speed > 19.8 km/h (HS19)	Underload vs. Sweet spot	−0.136	0.160	0.394	
	Underload vs. Danger zone	0.666 *	0.177	<0.001 *	0.76
	Sweet spot vs. Danger zone	0.802 *	0.095	<0.001 *	0.81
Speed > 25.2 km/h (HS25)	Underload vs. Sweet spot	−0.288 *	0.084	0.001 *	0.33
	Underload vs. Danger zone	0.359 *	0.109	0.001 *	0.34
	Sweet spot vs. Danger zone	0.646 *	0.099	<0.001 *	0.59
Mechanical work (MW)	Underload vs. Sweet spot	−0.241	0.142	0.091	
	Underload vs. Danger zone	0.423 *	0.159	0.008 *	0.48
	Sweet spot vs. Danger zone	0.664 *	0.092	<0.001 *	0.64

The asterisk symbol (*) is utilized to highlight significant differences.

Table 4. Z-score test flight time.

ACWR	Comparison	Mean Difference	Standard Error	*p*-Value	Cohen's d
Total Distance (TD)	Underload vs. Sweet spot	0.458	0.246	0.189	
	Underload vs. Danger zone	0.462	0.262	0.237	
	Sweet spot vs. Danger zone	−0.003	0.109	1	
Speed > 19.8 km/h (HS19)	Underload vs. Sweet spot	−0.303	0.172	0.237	
	Underload vs. Danger zone	0.279	0.19	0.429	
	Sweet spot vs. Danger zone	0.023	0.102	1	
Speed > 25.2 km/h (HS25)	Underload vs. Sweet spot	0.042	0.089	1	
	Underload vs. Danger zone	0.073	0.115	1	
	Sweet spot vs. Danger zone	0.031	0.105	1	
Mechanical work (MW)	Underload vs. Sweet spot	−0.102	0.151	1	
	Underload vs. Danger zone	0.116	0.169	1	
	Sweet spot vs. Danger zone	0.014	0.098	1	

Table 5. Z-score test contact time.

ACWR	Comparison	Mean Difference	Standard Error	*p*-Value	Cohen's d
Total Distance (TD)	Underload vs. Sweet spot	−0.214	0.244	1	
	Underload vs. Danger zone	0.58	0.261	0.079	
	Sweet spot vs. Danger zone	0.366	0.109	0.002 *	0.37
Speed > 19.8 km/h (HS19)	Underload vs. Sweet spot	−0.286	0.171	0.283	
	Underload vs. Danger zone	0.612	0.189	0.004 *	0.28
	Sweet spot vs. Danger zone	0.327	0.101	0.004 *	0.33
Speed > 25.2 km/h (HS25)	Underload vs. Sweet spot	0.091	0.088	0.906	
	Underload vs. Danger zone	0.184	0.115	0.327	
	Sweet spot vs. Danger zone	0.275	0.104	0.025 *	0.28
Mechanical work (MW)	Underload vs. Sweet spot	−0.045	0.15	1	
	Underload vs. Danger zone	0.363	0.167	0.092	
	Sweet spot vs. Danger zone	0.318	0.097	0.003 *	0.32

The asterisk symbol (*) is utilized to highlight significant differences.

4. Discussion

Previous research has primarily focused on evaluating running parameters while running and correlating them with biomechanical, neuromuscular, and metabolic manifestations of fatigue. Studies on wearable resistance training show that it has the potential to influence external load parameters while having no significant impact on internal load metrics such as heart rate or RPE. This highlights the effects of training interventions on biomechanical efficiency during running-specific movements [44]. There is some evidence that poor training-load management and prescription is a significant risk factor for injury [45]. Training-load-related injuries are widely regarded as largely preventable [11]. Monitoring protocols should address the issues of training-load management and prescription to improve performance and prevent injury at the same time. Field-based monitoring tools, such as GPS and accelerometers, provide actionable insights into athlete readiness, as demonstrated by recent research on wearable resistance and standardized runs [44,46].

In this study, on the other hand, we assessed the correlation with in-field athletic standard parameters. We analyzed whether there is any relationship between running parameters (Kvert, CT, FT) and ACWRs. Metrics such as Kvert, FT, and CT provide insight into the efficiency of an athlete's running mechanics. Our analysis indicates that FT does not differ significantly across groups, underscoring its limited utility in distinguishing between ACWR conditions. Conversely, CT primarily differentiates the group in the sweet spot from the danger zone group. K_{vert} appears particularly sensitive in distinguishing the danger zone group from the others. Specifically, K_{vert} values are consistently lower in the danger zone group than in the other groups, a difference that aligns with the core definition of vertical stiffness. Indeed, by definition [47–50], low stiffness values describe a run that does not have a "bouncing gait" and, therefore, is energetically ineffective [31,51]. Low vertical stiffness combined with low flight time and high contact time suggests that energy absorption is not being efficiently redirected into propulsion. This can reduce the running economy and increase joint strain. Instead, high stiffness values are typical of those having an energetically effective run and who manage to transform a large percentage of potential elastic energy acquired during the landing phase into the flight phase for the next step. Another possible explanation may be related to fatigue. Fatigue-related reductions in vertical stiffness, as reported in studies using both wearable resistance and standardized run assessments, further validate the importance of monitoring stiffness as an indicator of biomechanical and neuromuscular status during training [44,46]. The correlation between temporal parameter values and fatigue presents a crucial insight for coaches and practitioners seeking practical implications in training. As fatigue sets in, there is a notable reduction in vertical stiffness during a moderate intensity run, impacting an athlete's ability to efficiently convert potential elastic energy into propulsion [52,53].

Buchheit et al. [54] highlighted how running parameters like contact time (CT) and vertical stiffness (K) can be notably influenced by short-term neuromuscular fatigue when performing repeated high intensity runs. Furthermore, Winter et al. [30] observed that increasing levels of fatigue—particularly at higher speeds—often lead to lengthened contact times, suggesting a shift in neuromuscular coordination and a decline in running efficiency. Prigent et al. [55] documented that, in acute fatigue states, there are discernible rises in contact time, as well as a drop in vertical stiffness, indicating an adaptive response to neuromuscular constraints. Similarly, Apte et al. [56] noted that an increase in knee flexion angle at initial contact, associated with lower vertical stiffness, could serve as an alternate strategy to dampen impact forces.

This understanding underscores the importance of monitoring fatigue levels during training sessions [57]. To address this, coaches can integrate accelerometer/inertial sensor metrics, which offer heightened sensitivity to external load variables.

Future research should concentrate on the longitudinal assessment of vertical stiffness to better understand how it changes during different training and competitive phases. Examining how vertical stiffness adapts to various workloads could reveal important insights into biomechanical and neuromuscular adaptation in football players. Furthermore, investigating these changes during match scenarios, where the risk and severity of injuries are heightened, could provide valuable information for injury prevention strategies. Additionally, creating real-time monitoring systems to track vertical stiffness during training sessions and matches would give coaches and sports scientists valuable data.

5. Practical Applications

The adoption of vertical stiffness measurements could be a valuable tool to assess the neuromuscular load experienced by athletes. This approach presents several advantages: (1) it offers a practical and non-intrusive method to assess mechanical load without the need for additional, exhaustive testing, and (2) it allows for the identification of load differences between training sessions and competitions, providing objective insight into how athletes respond to various demands. By regularly monitoring vertical stiffness, coaches and physical trainers can fine-tune recovery strategies and better tailor training loads to each athlete's current condition, ultimately enhancing performance outcomes and reducing the risk of injury.

6. Conclusions

Valuable ideas have been presented concerning the analysis of the data collected on the elite players. The vertical stiffness values of the group in the danger zone are always lower than the others. The reason for this is that vertical stiffness may be associated with fatigue [52,53]. This study shows how it could provide athletic scientists with an additional tool for preventing workload-related injuries. Through these analyses, the study aims to identify potential differences in vertical stiffness among various workload ratio groups, thereby offering insights to inform evidence-based training programs tailored to the specific needs of individual athletes.

Author Contributions: S.P., M.M., S.F. and M.L. were responsible for the design of the study. S.P. and M.M. conducted the analyses and were responsible for data collection. All authors contributed to the interpretation of the findings and had full access to all data. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Institutional Review Board Statement: Approval for data collection was obtained from the club (as players' data were routinely collected over the course of the season). This study includes human participants and was approved by the University of Bologna Bioethics Committee (protocol No. 0351259 of 07/11/2024). The study was conducted in accordance with the Declaration of Helsinki (2013).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors on request.

Acknowledgments: The authors would like to thank the club Parma Calcio 1913 (medical staff, coaching staff, and all players) for their participation in the study.

Conflicts of Interest: The authors declare no conflicts of interest.

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