the Journal of Strength and Conditioning Research™

How Different Are Training Sessions From Matches? An Exploratory Study Analyzing Resultant Acceleration Distribution Curves of Portuguese Young Adult Male Soccer Players

Pedro Oliveira,[1] Ivan Baptista,[1,2] Felipe A. Moura,[3] Daniel Boullosa,[4,5,6] Ricardo Pimenta,[7,8,9,10] Fábio Y. Nakamura,[10,7,11] and José Afonso[1]

[1]Centre of Research, Education, Innovation, and Intervention in Sport (CIFI2D), Faculty of Sport, University of Porto, Porto, Portugal; [2]Department of Computer Science, Faculty of Science and Technology, UiT The Arctic University of Norway, Tromsø, Norway; [3]Laboratory of Applied Biomechanics, State University of Londrina, Londrina, Brazil; [4]Faculty of Physical Activity and Sports Sciences, Universidad de León, León, Spain; [5]Integrated Institute of Health, Federal University of Mato Grosso do Sul, Campo Grande, Brazil; [6]College of Healthcare Sciences, James Cook University, Townsville, Australia; [7]Research Center in Sports Sciences, Health Sciences and Human Development (CIDESD), University of Maia, Maia, Portugal; [8]Research Center of the Polytechnic Institute of Maia (N2i), Maia Polytechnic Institute (IPMAIA), Castêlo da Maia, Maia, Portugal; [9]Department of Rehabilitation and Performance Optimization (DROP), Futebol Clube Famalicão—Futebol SAD, Famalicão, Portugal; [10]FSI Lab, Football Science Institute, Granada, Spain; and [11]Graduate Program in Physical Education, Federal University of Pernambuco, Recife, Brazil

Abstract

Oliveira, P, Baptista, I, Moura, FA, Boullosa, D, Pimenta, R, Nakamura, FY, and Afonso, J. How different are training sessions from matches? An exploratory study analyzing resultant acceleration distribution curves of Portuguese young adult male soccer players. *J Strength Cond Res* XX(X): 000–000, 2026—This exploratory study examined the continuous distribution of acceleration (Acc) loads across a weekly microcycle in elite male youth soccer players, comparing training sessions with competitive match demands. Raw Acc data were processed to generate continuous distribution curves representing the frequency and magnitude of Acc across all sessions. Statistical Parametric Mapping was used to compare these distributions between match day (MD) and training days separately (MD-1 to MD-4). The results indicated that MD-3 and MD-4 showed the greatest similarity to match play, differing by only 0 and 134 points, respectively, on a 1,000-point scale, while MD-1 displayed the greatest divergence, consistent with its intended tapering function. The observed data suggest that MD-3 and MD-4 were the most physically demanding training sessions, closely replicating match demands, while the remaining days imposed lower Acc loads than match play. The continuous Acc approach provided detailed and context-specific evidence into how training sessions replicate or differ from competitive demands, overcoming the limitations of traditional threshold-based methods relying on arbitrary cutoffs. From a practical perspective, using continuous Acc values for intraindividual rather than interindividual comparisons may help strength and conditioning professionals to improve the precision of workload monitoring and support more individualized training adjustments based on intraindividual variability.

Key Words: accelerometer, load monitoring, continuous variables, microcycle

Introduction

Managing workload properly is important for helping players perform at their best and avoid injuries (1). Workload is commonly divided into internal (e.g., heart rate, rating of perceived exertion) and external (e.g., total distance, number of sprints) loads. Internal load refers to the psychophysiologic responses that occur during soccer play (18). Conversely, external load refers to parameters that are manipulated to generate an intended internal load, or parameters that are measured to infer internal load (19). Resultant acceleration (Acc) is one of the most frequently monitored external load parameters in soccer players (7,15,36), and includes positive (acceleration) and negative ("deceleration") changes in speed over time. These actions are critical because of their high mechanical and metabolic demands (24) and are commonly associated with fatigue and exercise-induced muscle damage, specifically in soccer (17). Moreover, from a physics perspective, Acc is defined as any change in velocity, which includes changes in both magnitude (speed) and direction. Resultant acceleration derived from triaxial inertial measurement units (IMUs), therefore, captures "complete acceleration," integrating speed-change acceleration during linear movements and direction-change acceleration generated during cuts, turns, and twists. This is particularly relevant in soccer, a multidirectional sport in which direction-change actions impose substantial mechanical stress (37) that may not be fully captured by traditional Global Positioning System (GPS)-derived speed-based acceleration metrics (34). Accordingly, IMU-derived Acc represents a more appropriate and comprehensive metric for quantifying the true mechanical workload in soccer.

Address correspondence to Pedro Oliveira, up201100413@edu.fade.up.pt.

Journal of Strength and Conditioning Research 00(00)/1–8

Although Acc captures the continuous spectrum of Acc (i.e., the load profile), overall mechanical load magnitude can also be summarized using metrics such as average Acc (10), which provide a single-value indication of total exposure. The procedure involves taking the absolute value of all Acc data and averaging over the duration of the defined period (e.g., match). It may be more appropriate for analyzing time-series data, where all Acc efforts are accounted for, regardless of the magnitude (11). This distinction between profile and magnitude is important for interpreting how training sessions replicate or differ from match demands.

Although Acc is a continuous variable, practitioners and researchers often rely on arbitrary and nonconsensual thresholds to categorize it (30), which lack biologic justification and are selected based on personal preference rather than a theory- or data-driven approach (23). Furthermore, statisticians have long cautioned against discretizing continuous data, because this practice leads to information loss, potentially resulting in reduced accuracy, sensitivity, and misleading conclusions (20). Analyzing Acc as an individualized and continuous variable, rather than according to predetermined categories, may be a more informative approach for monitoring an athlete's workload (31). In this approach, the natural differences between data points are preserved, avoiding distortions introduced by arbitrary thresholds that can group distant values together (e.g., 3.1 and 3.9 $m{\cdot}s^{-2}$) while separating closer values (e.g., 2.9 and 3.1 $m{\cdot}s^{-2}$) (30).

In the context of workload monitoring, it is essential to distinguish between the external workload imposed during official matches and that experienced throughout training sessions. Training loads should be appropriately planned and aligned with the specific demands of match play (33), but not all training sessions need to align with all game demands. Indeed, depending on the weekly goals and season phase, coaches may purposefully impose demands that deviate from typical match demands. At one end of the spectrum, coaches may wish to design recovery-focused weeks; at the other end, coaches may wish to generate overreaching periods, even at the risk of increasing fatigue during the next match (9). Strategically alternating overload and recovery days can better support adaptation (22). Still, managing training loads can benefit from considering match reference values, preferably individually quantified, acting as a reference point (1). Given the natural match-to-match variability, such reference values should be understood as ranges and not point values. For example, Acc showed a variability of approximately 12%, while total distance covered varied by ~5% across matches (3), reinforcing the idea that match demands are not fixed and should be contextualized. Studying the resulting Acc distribution curve, through a continuous-data approach, may offer a more effective approach to managing and prescribing training loads.

Regarding soccer microcycles, current research suggests that Acc training loads peak mid-week (8), followed by a tapering phase in the past 2 days before the game (7), but the interpretation of these data requires caution. For instance, when analyzing training loads in relation to match-day-minus/plus format (i.e., MD- and/or MD+), Martin-Garcia et al. (25) reported that absolute Acc values during training exceeded those recorded in competition for MD-4 (71–72%), MD-3 (62–69%), and MD-2 (56–61%), that is, players experienced higher Acc in training than in matches. However, these values were presented in relation to generic Acc thresholds, not applying a continuous-data approach. In contrast, Alonso-Callejo et al. (2) observed MD as the most demanding day, with players reaching higher relative Acc metrics compared with training sessions. However, reliance on categorical thresholds potentially masks the true Acc distribution during match play, as was discussed previously. Although Acc distributions are known to vary by position (31), little is known about how specific training days align with or diverge from match demands. In the context of interpreting training vs. match demands, it is important to consider that while continuous Acc distributions reveal the profile of mechanical loads, the magnitude, which could be summarized by average Acc, may differ between training sessions and matches. For example, MD-3 and MD-4 may closely replicate the distribution profile of match Acc demands, yet impose a slightly lower total mechanical load magnitude, which is relevant for practitioners when planning weekly microcycles.

Thus, this exploratory study aims to compare training and match demands by applying a continuous-data approach, using Acc from accelerometer-derived signals rather than from estimates based on positional changes obtained through the GPS. With this approach, we aim to overcome the limitations of arbitrary threshold-based analyses by adopting a continuous representation of Acc loads, thereby allowing for a more precise, context-specific understanding of training and match demands, and providing a clearer picture of how different sessions within the weekly microcycle replicate or diverge from the competitive profile. Therefore, the objective of this study was to compare the continuous Acc distributions between training and MD, and to identify which training sessions most closely reflect match demands among elite male youth soccer players.

Methods

Experimental Approach to the Problem

This longitudinal observational study examined elite youth soccer players to compare match loads with training loads using the MD-minus approach (e.g., MD minus 4 [MD-4], MD-3, etc.) through acceleration distribution curves, analyzed in both absolute and relative terms.

Subjects

A purposeful convenience sample recruited 37 male soccer players belonging to an elite soccer team (Tier 4 of the Participant Classification Framework (26)) competing in the "Liga Revelação" (Portuguese Under-23 development league) and in UEFA Youth League, during season 2023/2024. The sample was, therefore, adapted, constrained by squad size, player availability, and the requirement for complete observations across MD and all training days within the weekly microcycle. Aligned with the exploratory nature of the study, no predefined hypothesis was stipulated (12). In this context, traditional a priori or post hoc power calculations based on mean differences are not applicable. From the sample, 19 players (19.4 ± 0.9 years, 180 ± 0.06 cm, 75.6 ± 6.82 kg) met the inclusion criteria: (a) a minimum of 1 match played; and (b) at least 1 observation for each training day (i.e., MD) (Figure 1). Goalkeepers were excluded from the analysis, because their physical and movement profiles differ substantially from those of outfield players. The study covered 14 matches, totaling 882 individual observations, with an average of 63 observations per player (Table 1). The sample included 3 central defenders, 4 fullbacks, 5 central midfielders, 4 wide midfielders, and 3 strikers. Workload data were analyzed based on the number of days before or after an MD. The team rested on

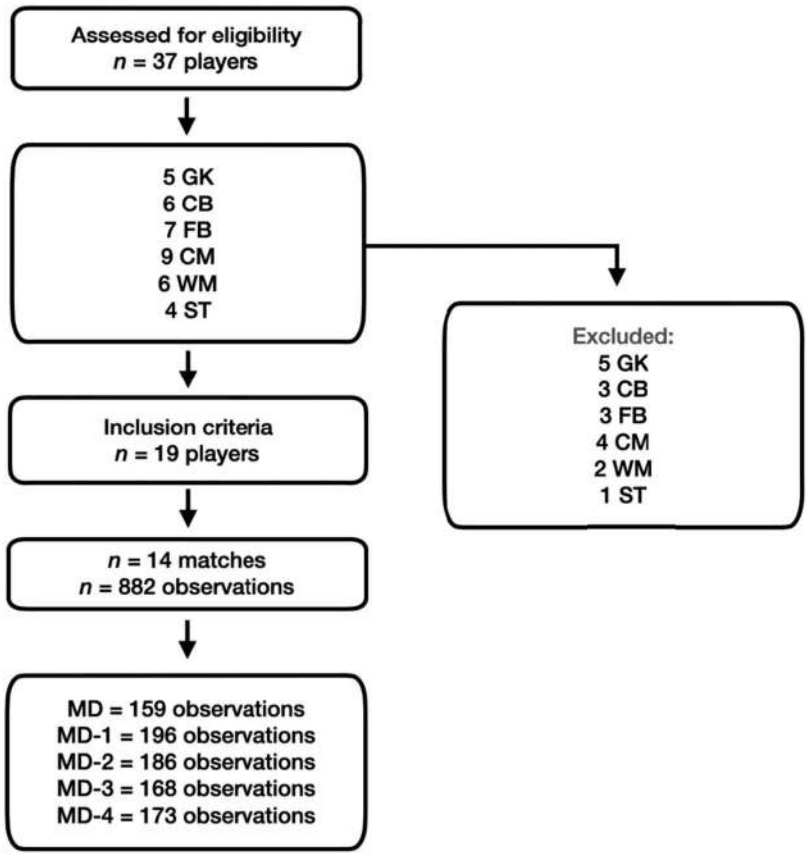

Figure 1. Flow diagram illustrating the selection process for the number of observations included in the study. Player positions are abbreviated as follows: central defenders (CD), fullbacks (FB), central midfielders (CM), wide midfielders (WM), and strikers (ST). Match day is referred as MD, with MD-1 to MD-4 indicating the number of days before the match.

MD+1—and those with higher match loads, who did not even go to the field—after recovery strategies or only taking part in active leisure activities such as footvolley, thus preventing any valid comparison with the match data. Anonymized data were collected retrospectively as part of the team's routine training monitoring process. Ethics Committee of the Faculty of Sport of the University of Porto approved the study (CEFADE 49-2022).

Training Design. The weekly microcycle followed a traditional structure with 4 main training days before the official match, MD-1 to MD-4 with each day characterized by specific training content and objectives established by the coaching staff. On MD-4, sessions emphasized small-sided games and drills in reduced spaces aiming to elicit frequent Acc and changes of direction under conditions of high mechanical load. On MD-3, training consisted primarily of large-sided games in extended pitch areas designed to replicate tactical and physical demands of competition with emphasis on high-intensity running and longer distances. On MD-2, the focus was on speed exercises and transitions, and on MD-1, training was limited to tapering, strategic organization, and set pieces.

Procedures

The GPS units were activated approximately 30 minutes before training or match kick-off to ensure optimal satellite connection. Each player wore a custom-made vest designed to position the GPS unit on the upper back, between the left and right scapulae. Players wore the same device across every session (35). At the end of each session, all GPS units were checked by the team's GPS manager and connected to a dock system to download the data. Acc data were recorded using a portable 100 Hz accelerometer

Table 1
Number of observations per week (W) and match day (MD).

MD	W1	W2	W3	W4	W5	W6	W7	W8	W9	W10	W11	W12	W13	W14	TOTAL
MD	13	13	10	11	14	14	14	11	9	13	14	13	0	10	**159**
MD-1	14	16	12	12	17	16	15	9	14	17	16	16	8	14	**196**
MD-2	12	14	14	14	17	16	11	11	12	15	14	13	12	11	**186**
MD-3	12	13	15	15	16	14	13	16	14	14	13	0	13	0	**168**
MD-4	12	15	13	13	16	14	14	12	14	13	13	14	10	0	**173**
TOTAL	**63**	**71**	**64**	**65**	**80**	**74**	**67**	**59**	**63**	**72**	**70**	**56**	**43**	**35**	882

Bolded values represent statistically significant differences ($p < 0.05$).

embedded in a FIFA-certified (1003407) GPS device (Catapult Vector S7, Catapult Sports, Melbourne, Australia). The device has recently demonstrated excellent inter- and intraunit reliability, with Intraclass Correlation Coefficient values near 1.00 and Coefficient of Variation (CV) between 3.7 and 4.7% for inertial movement analysis events, including accelerations, and CV $\approx$ 0.3% for measures of distance and speed in field-based simulations (21).

The data were then extracted using the manufacturer's software, excluding the initial 30 minutes after system connection (Catapult Openfield, version 3.10; Firmware 8.1). Resultant acceleration vector magnitude (AVMi) as a function of time was calculated from the x (lateral), y (frontal/back), and z (vertical) axis components (i.e., acx, acy, and acz, respectively) using the following formula (15):

$$AVM(i) = \sqrt{(acx_{i+1} - acx_i)^2 + (acy_{i+1} - acy_i)^2 + (acz_{i+1} - acz_i)^2}.$$

The use of resultant acceleration as an external load metric is supported by validation and reliability evidence for inertial movement analysis variables derived from triaxial inertial sensors, with excellent inter- and intraunit reliability reported in team sport contexts (21). This resultant vector reflects complete Acc, including changes in both movement speed and direction, and, therefore, captures the combined mechanical demands of linear and multidirectional actions characteristic of soccer.

Outcomes. The primary outcome was the comparison between match demands and training demands, assessed through the distribution of Acc across MD and training days (MD-1, MD-2, MD-3, MD-4). Acc distributions were quantified on a 1,000-point scale, considering both absolute values and relative frequencies. The secondary outcomes were the comparisons between training sessions (MD-1, MD-2, MD-3, MD-4), aimed at evaluating the degree of similarity or divergence in Acc distributions across the weekly microcycle. Differences were likewise expressed on a 1,000-point scale, focusing on both the volume and shape of the distributions.

Statistical Analyses

Raw data were exported from the manufacturer's software to MATLAB (R2024b 24.2.0) for further processing. We ran a histogram fit with 1,000 equally spaced points from a 0 to 10 g range, using a nonparametric kernel smoothing distribution, to create distribution curves of resultant Acc curve. Thus, each training or MD had a 1,000 point graph, where each point corresponded to the absolute and relative (%) frequency of the Acc value among the values already mentioned (0–10 g). To remove the effect of match and training duration and allow comparisons between days of different lengths, relative frequency was used to normalize absolute frequency. The figures (included in the Supplemental Digital Content, http://links.lww.com/JSCR/A795) illustrate where differences occur but do not depict the overall shape of the distribution curve. A kernel distribution is a nonparametric representation of the probability density function of a given variable. It is recommended when a parametric distribution cannot correctly describe the data or to avoid making assumptions about the distribution of the data (5).

Statistical Parametric Mapping (SPM) was used to compare the different days to each other (e.g., the average of all MD+1 vs. the average of all MD). Statistical Parametric Mapping is used to perform a specific statistical analysis of time series and curves and has previously been applied to biomechanical time-series data in soccer kicking, running, cutting, and landing techniques (39). An SPM 1-way analysis of variance, with Bonferroni post hoc tests, was used to identify significant differences between days. The significance level adopted was $p \leq 0.05$ to detect differences between conditions. Given the possibility of a high number of comparisons, reporting each individual p-value is not feasible. Instead, results are illustrated using SPM plots, which visually indicate the acceleration ranges where statistically significant differences were identified across the 1,000-point curve.

Results

Main Outcomes: Comparison Between Training and Match Demands

The comparison of Acc distributions between MD and the training days revealed distinct patterns of distributional profiles (Table 2). There were differences in absolute frequencies between the different training days and MD, but these were substantially reduced when relative frequency (i.e., removing the effect of session duration) was used. For instance, MD-1 differed from MD by 712 points in absolute terms, but only 395 points in relative terms, and MD-2 decreased from 564 to 0 points.

Among the training days, MD-3 and MD-4 showed the closest Acc distributions to the match, whereas the other sessions diverged more substantially. On a 1,000-point scale, MD-3

Table 2

Number of differing points (on a 1,000-point scale) between the absolute and relative (%) Acc distribution of match-day (MD) and each training day across 14 weeks of observation.

	MD-1		MD-2		MD-3		MD-4	
Matchday	Absolute	Relative	Absolute	Relative	Absolute	Relative	Absolute	Relative
MD	856	658	712	395	564	0	660	134
MD-1			556	73	690	542	623	472
MD-2					459	315	254	209
MD-3							260	2

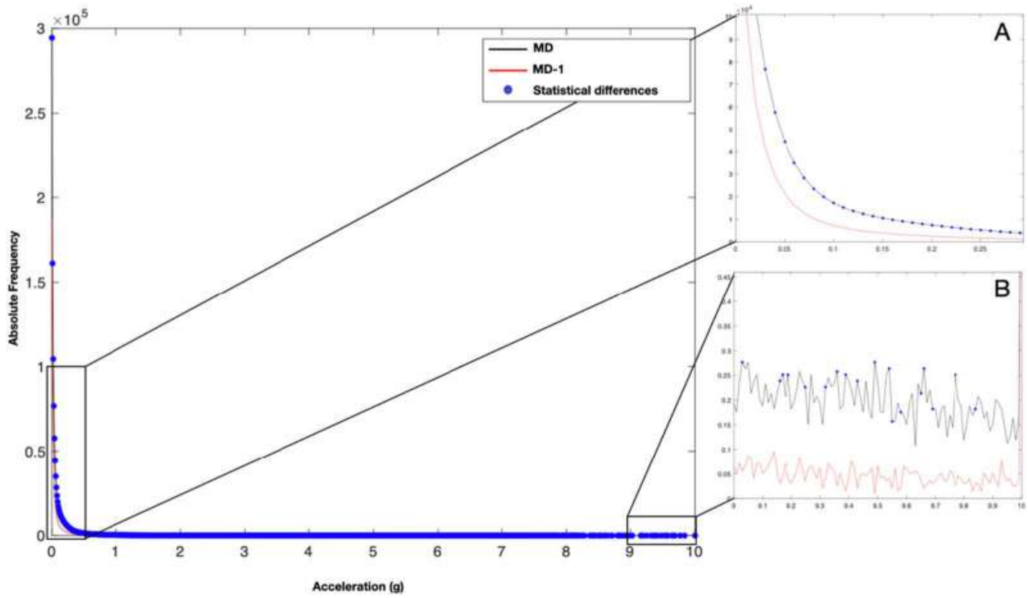

Figure 2. Example of comparison between an average of absolute frequency of MD (variable A, black line) and MD-1 (variable B, red line) Acc demands curves, based on a 1,000-point distribution. Blue dots indicate statistically significant differences. (A) refers to a zoom-in reduced *x*-scale (0–0.5 g) and *y*-scale indicating absolute frequency of Acc. Overall, match demands were consistently higher than training loads, and smoother appearance of the curves is observed. (B) Refers to a zoomed-in reduced *x*-scale (9–10 g) and *y*-scale indicating absolute frequency of Acc, showing that when inspecting the curves at a finer scale, a noisier and more variable shape is observed.

displayed no difference from MD (0 points), while MD-4 showed a similar number, with a difference of only 134 points, suggesting that these training days more closely replicate match demands with respect to Acc. Notably, the Acc distributions on MD-3 and MD-4 were similar in shape and overall volume, with slightly lower Acc loads than those of the match. Figures 2 and 3 (with absolute and relative frequency of Acc, respectively) provide a representative example of these patterns (with additional comparisons available in the Supplemental Digital Content, http://links.lww.com/JSCR/A795): section A illustrates the smoother behavior of the curve at lower Acc ranges, while section B shows its more irregular and variable appearance at higher ranges. This suggests that both days closely align with the demands of competition.

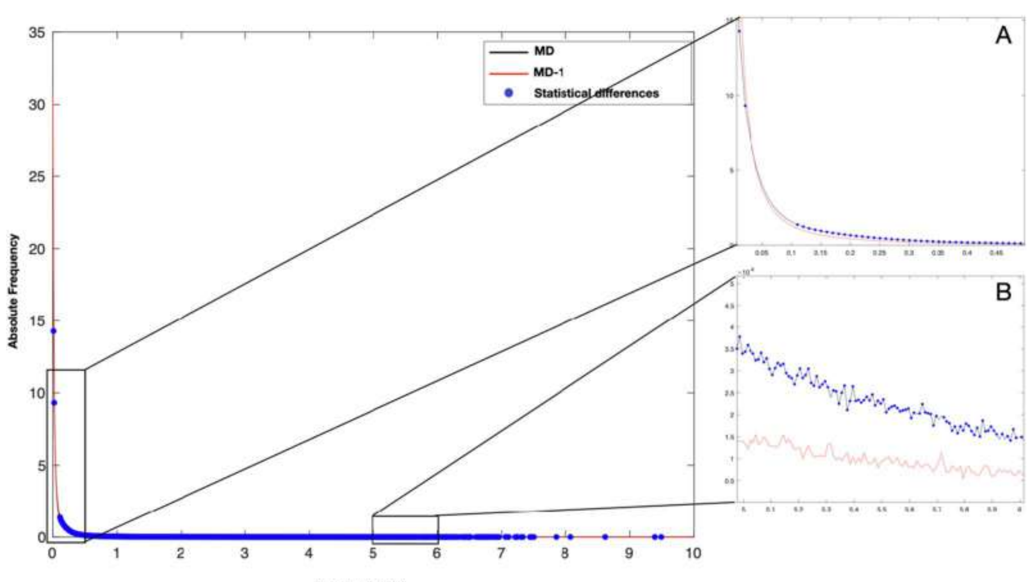

Figure 3. Example of comparison between an average of relative frequency of MD (variable A, black line) and MD-1 (variable B, red line) Acc demands curves, based on a 1,000-point distribution. Blue dots indicate statistically significant differences. (A) Refers to a zoom-in reduced *x*-scale (0–0.5 g) and *y*-scale indicating relative frequency of Acc. Overall, match demands were consistently higher than training loads and smoother appearance of the curves is observed. (B) Refers to a zoom-in reduced *x*-scale (5–6 g) and *y*-scale indicating relative frequency of Acc, showing that when inspecting the curves at a finer scale, a noisier and more variable shape is observed.

Match Day-2 demonstrated a lower frequency of Acc efforts, especially in lower Acc ranges, compared with the match, reflecting a lower similarity (Figures 2 and 3). The greatest divergence was found between MD and MD-1, where the Acc profile was not only different in shape but also showed a clear underrepresentation of high-acceleration bouts, indicating that MD-1 provides the least comparable stimulus to match play.

Secondary Outcomes: Comparisons Between Training Sessions

Comparisons between training sessions revealed a progressive reduction in Acc distribution throughout the week. Specifically, the smallest difference was observed between MD-3 and MD-4 (2 points on a 1,000-point scale), indicating a high degree of similarity between these days. The difference between MD-1 and MD-2 was 73 points, also reflecting relative similarity. The remaining comparisons showed more pronounced differences: MD-1 differed from MD-3 and MD-4 by 542 and 472 points, respectively, while MD-2 differed from MD-3 by 315 points and from MD-4 by 209 points.

Discussion

This exploratory study offers insights into training load continuous distributions across different microcycles by comparing the demands of each training day within the microcycle with those observed during match play, with a focus on Acc profiles. The main findings suggested that MD-3 and MD-4 were the training days most similar to match demands, while MD-1 was characterized by the greatest divergence from competition loads. Furthermore, almost all training days, except MD-3, imposed lower Acc demands than match play. The observed distribution seems to align with conventional training load programming across the microcycle, a pattern that is also reflected in previous studies, even those that applied arbitrary thresholds to categorize Acc.

Our results hinted that MD-3 and MD-4 exhibit the greatest similarity to match demands, as reflected by the minimal differences in Acc distributions when compared with match data. A possible explanation for these results could be that MD-4 sessions emphasized small-sided games aimed at increasing the frequency of Acc, while on MD-3, training was designed to replicate tactical and physical match demands. This trend is consistent with previous studies, which have shown that MD-3 and MD-4 are typically structured to deliver the most physically demanding sessions of the microcycle, with respect to Acc, aiming to reproduce the competitive demands that players face during match play (25). Ravé et al. (33) emphasize the need to include training sessions that closely replicate match demands. A fine-tuning monitoring approach is suggested, using the best combination of valid and practical tools, instead of a single tool, to improve the effectiveness of monitoring practices in each specific context (4). Therefore, we may suggest the use of psychophysiologic data in conjunction with the current Acc to provide a better understanding of training and competitive loading and subsequent adaptation.

Conversely, MD-1 demonstrated the greatest divergence, characterized by a notable underrepresentation of Acc efforts. Specifically, on MD-1, team training was limited to tapering, organizational strategies, and set pieces. These results align with previous research emphasizing the importance of tapering strategies, which are adopted by coaches as an attempt to decrease the stress of training and maximize performance (29).

All differences between training sessions and MD were consistently in favor of match play, indicating that match play imposes greater Acc demands than training sessions. Figure 2 showed the shape of the curve in the lower and higher absolute Acc ranges, where the profile seems smoother in lower Acc ranges (Figure 2A), while in higher ranges, the curve seems notably more irregular and variable (Figure 2B). As previous studies have demonstrated, the high frequency of lower Acc values suggests that common actions such as walking, running, and slight directional changes are predominant (31), while higher Acc values are less frequent, reflecting the more sporadic but high-intensity efforts that players typically perform during competitive match play (16). These findings hint that while MD-3 and MD-4 may serve as suitable days for replicating match-specific demands, MD-1 seems to be the day that deviates the most from match demands in terms of Acc loads.

The normalization process to remove the effect of time, in which relative frequency was applied to normalize absolute frequency, was particularly important, because session duration can strongly influence absolute Acc counts. In absolute terms, longer sessions naturally accumulate a greater number of Acc events, even when the relative intensity and effort structure are comparable. For example, when analyzed in absolute terms, MD-3 differed from match play by 564 points, while MD-4 differed by 660 points on a 1,000-point scale. However, when normalized to relative frequency (%), these differences dropped dramatically—to 0 and 134 points, respectively—indicating that, despite lower total exposure, the *distribution pattern* of Acc during MD-3 and MD-4 closely replicated match demands. Conversely, MD-1 remained markedly different under both approaches (856 absolute vs. 658 relative points), consistent with its tapering role within the microcycle.

Previous research has emphasized that the majority of variability in training load measures is explained by session duration (~60–70%), hiding the true differences in physical demands (38). This demonstrates how absolute analyses may overemphasize total workload because of longer duration or higher activity volume, while relative analyses better capture how the *intensity distribution* within a session compares with match play. In practical terms, a coach might consider MD-3 and MD-4 as the key sessions to reproduce match-like Acc patterns, even though their total load is lower than that of the game. Therefore, normalizing Acc data by duration provides a more accurate representation of the load distribution profile and enables meaningful comparisons between training and match contexts.

The similarity between MD-3 and MD-4 (a 2-point difference on a 1000-point scale) may reflect specific methodological strategies used during training on these days. For instance, MD-4 sessions often emphasize neuromuscular stimulation through small-sided games and priming strategies (32), while MD-3 sessions may prioritize tactical work in larger spaces to promote high-speed actions (6). Even though some authors suggest that these distinct approaches can result in comparable external load profiles across both days (13), MD-3 and MD-4 typically serve distinct training objectives; therefore, their locomotor patterns would be expected to differ substantially. This observed similarity between MD-3 and MD-4 highlights the strength of the continuous Acc profiling method in capturing cumulative mechanical load, which is the major factor of fatigue and conditioning. Although MD-3 emphasizes high-speed linear running and MD-4 involves frequent multidirectional changes, the overall distribution of mechanical work across these sessions is statistically equivalent. This suggests that continuous Acc profiles provide a robust representation of total mechanical stress, while traditional analyses based on distance or speed can still complement this approach to distinguish underlying locomotor patterns when needed. This interpretation aligns with the concept of a hybrid analytical framework proposed in previous work, in which continuous and individualized analyses are recommended but should be complemented with more traditional, threshold-based methods (30).

A relative similarity was also observed between MD-1 and MD-2 (a 73-point difference), which may reflect a deliberate reduction in training load during the final days of the microcycle before competition. Specifically, MD-2 often initiates tactical preparation for the upcoming match, while MD-1 typically involves a substantial tapering of physical demands (7). In training sessions closer to the MD, training exercises should be carefully chosen to avoid excessive Acc demands, consistent with this tapering strategy (36).

The observed data suggest that MD-3 and MD-4 were identified as the most physically demanding training sessions, closely replicating match demands, while the other days imposed lower Acc demands than match play. This aligns with findings from previous studies, which reported similar differences between training and match demands (27,36). This is an important finding: if training sessions impose similar Acc demands to those of match play, players are not only challenged with maximal Acc loads during competition, thereby enhancing their ability to tolerate such demands, improving performance, and preventing injury risks. However, some authors argue against this pattern, because training should also prioritize recovery and avoid constant exposure to maximal loads between matches (14,29). The continuous Acc approach used in this exploratory study may offer an alternative way to monitor the days that reproduce the demands of the game in terms of Acc distribution, although this pattern may not necessarily emerge when analyzing GPS variables at different intensity ranges. Moreover, using continuous Acc values for intraindividual rather than interindividual comparisons may improve the accuracy of workload monitoring, help prevent under- or overestimation of physical loads, and support more tailored training adjustments based on intraindividual variability (30).

It is important to acknowledge the limitations of this study. First, the exploratory nature of this study and the relatively small number of players limit the generalizability of the findings. Although the data set included a large number of individual observations collected longitudinally across multiple weeks, future studies should aim to replicate these analyses in larger samples and across different competitive levels. Second, the analysis did not include the postmatch day (MD+2), which could provide important insights into the recovery process after MD, as well as the compensatory training load typically prescribed to nonstarting players on these days (28). Third, the sample consisted exclusively of highly trained male youth soccer players. It is possible that different patterns of Acc distribution and training–match relationships may emerge in senior professionals, female athletes, or teams competing in different leagues or countries with varying tactical and physical demands. Therefore, the generalizability of the findings should be approached with caution, as the observed results may be specific to the team and competitive context analyzed. Future research should aim to explore complete weekly training cycles, including both postmatch recovery and prematch preparation days, to better understand the relationship between weekly load and match demands.

Practical Applications

This exploratory study suggests that continuous Acc profiles (i.e., avoiding arbitrary thresholds) may be a useful tool to evaluate the degree of similarity between training and match demands. Matchday-3 and MD-4 were identified as the most physically demanding training sessions, closely replicating match demands, while MD-1 showed the greatest divergence, possibly because of tapering strategies. This approach could enhance the monitoring and adjustment of training loads in relation to competition, helping strength and conditioning professionals to improve workload precision and to individualize training based on intraindividual variability.

Acknowledgments

CIFI2D is financed by the Portuguese Foundation for Science and Technology, under the DOI https://doi.org/10.54499/UIDB/05913/2020 and F. A. Moura is currently supported by the Brazilian National Council for Scientific and Technological Development (CNPq) under Grants 401004/2022-8, 200290/2022-3, and 305997/2022-0. No additional financial support is declared. Research concept and study design—P. Oliveira, I. Baptista, F. Y. Nakamura, J. Afonso; literature review—P. Oliveira, I. Baptista, D. Boullosa, F. Y. Nakamura, J. Afonso; data collection—P. Oliveira, F. A. Moura, R. Pimenta; data analysis and interpretation—P. Oliveira, F. A. Moura, R. Pimenta, J. Afonso; statistical analyses—P. Oliveira, F. A. Moura, R. Pimenta; writing of the article—P. Oliveira, I. Baptista, D. Boullosa, F. Y. Nakamura, J. Afonso; editing a draft of the article—P. Oliveira, D. Boullosa, F. Y. Nakamura, J. Afonso.

References

1. Akenhead R, Nassis GP. Training load and player monitoring in high-level football: Current practice and perceptions. *Int J Sports Physiol Perform* 11: 587–593, 2016.
2. Alonso-Callejo A, García-Unanue J, Perez-Guerra A, et al. Effect of playing position and microcycle days on the acceleration speed profile of elite football players. *Sci Rep* 12: 19266, 2022.
3. Baptista I, Winther AK, Johansen D, Randers MB, Pedersen S, Pettersen SA. The variability of physical match demands in elite women's football. *Sci Medicine Football* 6: 559–565, 2022.
4. Boullosa D, Claudino JG, Fernandez-Fernandez J, et al. The fine-tuning approach for training monitoring. *Int J Sports Physiol Perform* 18: 1374–1379, 2023.
5. Bowman AW, Azzalini A. Applied smoothing techniques for data analysis. *Comput Stat* 15: 301–302, 1997.
6. Caro E, Lapuente-Sagarra M, Caparrós T, Iglesias X, Ruiz-Sanchis L. Analysis of submaximal intensity periods during the competitive microcycle in professional footballers [Análisis de los periodos de intensidad submáxima durante el microciclo competitivo en futbolistas profesionales]. *Apunts Educación Física y Deportes* 158: 52–62, 2024.
7. Clemente FM, Owen A, Serra-Olivares J, Nikolaidis PT, van der Linden CMI, Mendes B. Characterization of the weekly external load profile of professional soccer teams from Portugal and the Netherlands. *J Hum Kinet* 66: 155–164, 2019.
8. Coutinho D, Gonçalves B, Figueira B, Abade E, Marcelino R, Sampaio J. Typical weekly workload of under 15, under 17, and under 19 elite Portuguese football players. *J Sports Sci* 33: 1229–1237, 2015.
9. Coutts AJ, Reaburn P, Piva TJ, Rowsell GJ. Monitoring for overreaching in rugby league players. *Eur J Appl Physiol* 99: 313–324, 2007.

10. Delaney JA, Cummins C, Thornton HR, Duthie GM. Importance, reliability and usefulness of acceleration measures in team sports. *J Strength Cond Res* 32: 3485–3493, 2018.
11. Delaney JA, Duthie GM, Thornton HR, Scott TJ, Gay D, Dascombe BJ. Acceleration-based running intensities of professional rugby league match-play. *Int J Sports Physiol Perform* 11: 802–809, 2016.
12. Ditroilo M, Mesquida C, Abt G, Lakens D. Exploratory research in sport and exercise science: Perceptions, challenges, and recommendations. *J Sports Sci* 43: 1108–1120, 2025.
13. Douchet T, Paizis C, Carling C, Babault N. Influence of a modified versus a typical microcycle periodization on the weekly external loads and match day readiness in elite academy soccer players. *J Hum Kinet* 93: 133–144, 2024.
14. Gabbett TJ. The training-performance puzzle: How can the past inform future training directions? *J Athl Train* 55: 874–884, 2020.
15. Gómez-Carmona CD, Bastida-Castillo A, Ibáñez SJ, Pino-Ortega J. Accelerometry as a method for external workload monitoring in invasion team sports. A systematic review. *PLoS One* 15: e0236643, 2020.
16. Gualtieri A, Rampinini E, Iacono AD, Beato M. High-speed running and sprinting in professional adult soccer: Current thresholds definition, match demands and training strategies. A systematic review. *Front Sport Active Living* 5: 1116293, 2023.
17. Hader K, Rumpf MC, Hertzog M, Kilduff LP, Girard O, Silva JR. Monitoring the athlete match response: Can external load variables predict postmatch acute and residual fatigue in soccer? A systematic review with metaanalysis. *Sports Med Open* 5: 48, 2019.
18. Impellizzeri F, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *Int J Sports Physiol Perform* 14: 270–273, 2019.
19. Jeffries A, Marcora S, Coutts AJ, Wallace L, McCall A, Impellizzeri FM. Development of a revised conceptual framework of physical training for measurement validation and other applications. *Sports Med* 52: 709–724, 2022.
20. Losciale J, Truong LK, Ward P, Collins GS, Bullock GS. Limitations of separating athletes into high or low-risk groups based on a cut-off. A clinical commentary. *Int J Sports Phys Ther* 19: 1151–1164, 2024.
21. Mackay L, Sawczuk T, Jones B, Darrall-Jones J, Clark A, Whitehead S. The reliability of a commonly used (CatapultTM Vector S7) microtechnology unit to detect movement characteristics used in court-based sports. *J Sports Sci* 43: 555–564, 2025.
22. Malone J, Di Michele R, Morgans R, Burgess D, Morton JP, Drust B. Seasonal training-load quantification in elite English Premier League soccer players. *Int J Sports Physiol Perform* 10: 489–497, 2015.
23. Malone J, Lovell R, Varley MC, Coutts AJ. Unpacking the black box: Applications and considerations for using GPS devices in sport. *Int J Sports Physiol Perform* 12: S218–S226, 2017.
24. Martín-García A, Casamichana D, Díaz AG, Cos F, Gabbett TJ. Positional differences in the most demanding passages of play in football competition. *J Sports Sci Med* 17: 563–570, 2018.
25. Martin-Garcia AS, Gómez Díaz A, Bradley PS, Morera F, Casamichana D. Quantification of a professional football team's external load using a microcycle structure. *J Strength Condi Res* 32: 3511–3518, 2018.
26. McKay AKA, Stellingwerff T, Smith ES, et al. Defining training and performance caliber: A participant classification framework. *Int J Sports Physiol Perform* 17: 317–331, 2022.
27. Moreno-Azze A, Rodán P, de la Fuente FP, Falcón-Miguel D, Gómez-Carmona CD. Differences in accelerations and decelerations across intensities in professional soccer players by playing position and match-training day. *Appl Sci* 15: 8936, 2025.
28. Nobari H, Sogut M, Oliveira R, et al. Wearable inertial neasurement unit to accelerometer-based training monotony and strain during a soccer season: A within-group study for starters and non-starters. *Int J Environ Res Publ Health* 18: 8007, 2021.
29. Oliva-Lozano JM, Gómez-Carmona CD, Fortes V, Pino-Ortega J. Effect of training day, match, and length of the microcycle on workload periodization in professional soccer players: A full-season study. *Biol Sport* 39: 397–406, 2022.
30. Oliveira P, Baptista I, Moura FA, et al. Mixing the sheep and the goats: Reframing the interpretation of acceleration data in sport. *Int J Sports Physiol Perform* 21: 330–333, 2025.
31. Oliveira P, Moura FA, Baptista I, Nakamura FY, Afonso J. Variation in accelerometer-derived instantaneous acceleration distribution curves of elite male soccer players according to playing position: A pilot study. *Sports (Basel)* 12: 263, 2024.
32. Peña J, Colomar J, Piedra A, Vicens-Bordas J, Altarriba-Bartés A. Exercise-based priming in team sports: Practical guidelines for enhancing neuromuscular readiness and reducing injury risk. *ScienceDirect* 61; 100498, 2025.
33. Ravé G, Granacher U, Boullosa D, Hackney AC, Zouhal H. How to use global positioning systems (GPS) data to monitor training load in the "real world" of elite soccer. *Front Physiol* 11: 944, 2020.
34. Sandmael S, Dalen T. Comparison of GPS and IMU systems for total distance, velocity, acceleration and deceleration measurements during small-sided games in soccer. *Cogent Soc Sci* 9, 2023.
35. Scott MTU, Scott TJ, Kelly VG. The validity and reliability of global positioning systems in team sport: A brief review. *J Strength Cond Res* 30: 1470–1490, 2016.
36. Silva H, Nakamura FY, Beato M, Marcelino R. Acceleration and deceleration demands during training sessions in football: A systematic review. *Sci Medicine Football* 7: 198–213, 2023.
37. Singh U, Leicht AS, Connor JD, et al. Biomechanical determinants of change of direction performance: A systematic review. *Sports Med* 55: 2207–2224, 2025.
38. Weaving D, Barron-Dalton N, McLaren S, et al. The relative contribution of training intensity and duration to daily measures of training load in professional rugby league and union. *J Sports Sci* 38: 1674–1681, 2020.
39. Whyte EF, Richter C, O'connor S, Moran KA. The effect of high intensity exercise and anticipation on trunk and lower limb biomechanics during a crossover cutting manoeuvre. *J Sports Sci* 36: 889–900, 2017.