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# The effects of congested fixture periods on distance-based workload indices: A full-season study in professional soccer players

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**ABSTRACT:** The aim of this study was to compare distance-based workload indices during congested fixture periods among different levels of participation in matches. Nineteen elite professional male players (age: 26.5 ± 4.3 years) from a European First League team were monitored daily over a full season using global positioning measurements. Distance-based measures (total distance, high-intensity running, high-speed running distance, and number of sprints) were collected daily. The following workload indices were calculated weekly: (i) acute load; (ii) acute : chronic workload ratio; (iii) training monotony; and (iv) training strain. During the season, seven congested weeks were selected. The participation levels of the players were categorized as starting in three matches (S3M), two matches (S2M), or one match (S1M) in the same week. Comparisons of the workload indices between levels of participation revealed that the acute load of total distance was significantly greater for S2M than S1M (+27%) and for S3M than for S1M (+30%). Moreover, the acute load of high-speed running was significantly greater for S2M than for S1M (+79%) and for S3M than for S1M (+60%). The acute load of high-intensity running was also significantly greater for S2M than for S1M (+54%) and for S3M than for S1M (+67%). This study revealed that acute load and training strain were meaningfully greater for S2M and S3M than S1M, although no significant differences were found between S1M, S2M, and S3M for the overall distance measures in terms of acute : chronic workload ratio and training monotony.

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## INTRODUCTION

Training load monitoring is considered an important part of individualized approaches to team sports training that allows coaches to quickly control and identify needs for adjusting the stimulus (1). The load units can be monitored in two forms (2): (i) external load (which is associated with the physical demands and mechanical work related to the exercise imposed on players) and (ii) internal load (which is related to the psychobiological changes occurring in response to the external load). Both dimensions are closely associated, although they provide different information about the impact of a training session on players (3). A well-implemented player monitoring cycle can help to control load if core sports training principles (e.g., individualization, progression, overload, variability of stimuli) are considered (4). Moreover, a monitoring cycle may be used to infer possible overreaching, undertraining situations, or exposure to injury risks (5).

One of the hypothetical causes of increased injury risk among players is spikes in the acute load (accumulated load of a week) caused by training in relation to the previous weeks (6). These spikes are characterized by a large increase in acute load in comparison to chronic load (accumulated load of the past weeks); thus, it does not adhere to the training principle of progressive overload (7). Nevertheless, the cause-effect relationship (between spikes in load and an increase in injury risk) may not be so straightforward since there are some confounding variables (e.g., clinical history, trainability, recovery, habituation to chronic load). In fact, some moderating factors might reduce the occurrence of injuries in those situations (8). As an example, having good aerobic fitness and playing experience can protect against rapid changes in acute : chronic workload ratio [ACWR] (> 2.0 A.U.) in elite Gaelic football players (9). Similar evidence was revealed in soccer, as a better intermittent aerobic fitness was found to be an important moderator factor against spikes in high-speed running (10). However, not only can having a good fitness level bolster a player's resilience to spikes in load; it can also be necessary to progressively increase the chronic load (11) to avoid, as example, a spike in the transition from a regular to a congested week.

Examining the relationship between acute and chronic load is a good approach to understanding the progression and overload training principles. However, other important principles can also be analysed using different indices. One such index is training monotony (first introduced as daily mean load divided by standard deviation), which represents the variability level of training load within the week (12). In the same article (12), training strain was also represented as the product of weekly training load (acute load) and training monotony. These two indices (training monotony and strain) might also be important indices to employ when controlling players' exposure to chronic high doses and low variability levels, both of which hinder proper recovery (13).

Considering the impact of soccer on socio-economics interests, this fact has been derived from many official competitions, the influence of competitive schedules (14), and, subsequently, the increase of congested fixture (typically, weeks with two matches or more with less than 72 hours between matches). Under such conditions, the time needed for recovery has decreased (15). The occurrence of congested fixture periods can conflict with a proper recovery schedule (caused by cumulative fatigue and a lack of muscle recovery), thus increasing players' susceptibility to injury (16). Among other factors, congested fixtures seem to contribute to decreases in muscle stiffness (17), increases in strength deficits (18), and increases in physiological stress and muscle damage (19). As an example, in a simulated period of soccer-specific fixture congestion in semi-professional players, significantly lower knee flexor peak torque was found in the two simulated matches after the first one while muscle soreness significantly increased, despite no changes in the player load metric during running (20). In a real scenario of short-term fixture, a study conducted in professional players revealed that low and medium intensities and sprint distances were meaningfully different across the matches and that such differences were also revealed between playing positions (21). Despite the growing evidence about the effects of the congested fixture (15), there is, however, a lack of information about the consequences of these periods for the overall load that players are exposed to during the week (considering both matches and training sessions).

Load monitoring (in particular, in the external dimension) using ACWR has been extensively researched in the past (7). Nevertheless, there is a lack of information about ACWR, training monotony, and strain values within congested fixture periods. Possibly, the use of ACWR could be important to better characterize these periods in terms of their influence on the external load indices. However, it is important to examine the influence of different levels of participation on variations in external load indices during a congested schedule. Being a starter in different levels of participation (a starter in one, two or three matches during a congested week) may represent a meaningful difference in terms of load (considering that matches have the greatest impact on players and that some of the starter players in fewer matches (in comparison to those playing in all the matches as a starter during the congested period) do not have additional training to "replace" the match). Considering that a match may demand 10–14 km of total distance and up to 1000 m of high-speed running (22), and considering that a typical training week with four sessions may represent ~450 m of high-speed running and 20 km of total distance (23, 24), this may suggest a loss of about 40–50% (gross numbers) of the load for those who did not play (or played in fewer matches) and did not have supplementary training to replace the match.

For the reasons mentioned above, and in an attempt to better characterize the impact of congested fixture periods on external load indices in different levels of participation as a starter, the purpose of this study was to analyse the variations of acute load, ACWR, training monotony, and training strain of distance-based measures at different levels of participation in matches (i.e., one, two, and three matches per week) in a professional soccer team.

## MATERIALS AND METHODS

### *Experimental approach to the problem*

This study followed a descriptive research design. Professional soccer players were monitored daily during a full season (from July 3, 2018, to May 9, 2019). During the period, 45 weeks were monitored despite only the competitive period (in-season) being considered for the analysis (considering the purpose of the study). Weeks were classified as either congested (two matches or more within a seven-day period) or regular (one match within a seven-day period). The period of analysis included 38 regular weeks and seven congested weeks (Table 1).

The congested weeks were characterized based on the number of sessions between the two (or more) matches. Moreover, the number of regular weeks before the congested week was counted (to better characterize the context before each congested week) and considered only for the effect of calculating the chronic load during the congested weeks. Based on their participation in a match (25), players were classified either as (i) starters in three matches (S3M: started in three matches in a congested week and played at least 45 min in each of these three matches); (ii) starters in two matches (S2M: started in two matches in a congested week and played at least 45 min in each of these two matches); and (iii) starters in one match (S1M: started in one match in a congested week and played

**TABLE 1.** Number of sessions, matches, regular weeks (RW) and congested weeks (CW) during each month within the season.

| | Jul. | Aug. | Sept. | Oct. | Nov. | Dec. | Jan. | Feb. | Mar. | Apr. | May |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Sessions (n) | 32 | 22 | 19 | 19 | 22 | 21 | 20 | 15 | 19 | 18 | 5 |
| Matches (n) | 5 | 5 | 4 | 4 | 3 | 7 | 6 | 4 | 4 | 4 | 2 |
| RW (n) | 4 | 3 | 3 | 5 | 5 | 2 | 3 | 3 | 4 | 4 | 4 |
| CW (n) | 1 | 1 | 1 | 0 | 0 | 2 | 2 | 1 | 0 | 0 | 0 |

Jul: July; Aug: August; Sept: September; Oct: October; Nov: November; Dec: December; Jan: January; Feb: February; Mar: March; Apr: April

**TABLE 2.** Characteristics of each congested week included in the analysis.

| | CW1 | CW2 | CW3 | CW4 | CW5 | CW6 | CW7 |
|---|---|---|---|---|---|---|---|
| Month | 08 | 09 | 12 | 12 | 01 | 01 | 02 |
| Training sessions between matches (n) | 2 | 2 | 2 | 2 | 3 | 3 | 2 |
| Regular weeks before (n) | 2 | 2 | 5 | 2 | 0 | 2 | 0 |
| Starters in three matches (n) | 3 | 4 | 6 | 6 | 2 | 4 | 4 |
| Starters in both matches (n) | 6 | 4 | 2 | 3 | 8 | 4 | 6 |
| Starters in one match (n) | 8 | 6 | 2 | 2 | 4 | 6 | 3 |

CW: congested week

at least 45 min in that match). The full characteristics of the congested weeks can be observed in Table 2.

The acute load (accumulated load throughout a week), acute : chronic workload ratio, training monotony, and training strain were calculated weekly during the season for each of the distanced-based measurements, which were recorded using 18-Hz global positioning systems (GPSs).

### *Participants*

Nineteen elite professional male players (age: 26.5 ± 4.3 years; body mass: 75.6 ± 9.6 kg; height: 180.2 ± 7.3 cm; experience as professionals: 7.5 ± 4.3 years) from a European First League team participated in this study. Players were categorized based on their playing position as external defenders (ED, n = 3), central defenders (CD, n = 4), midfielders (MF, n = 6), external midfielders (EM, n = 4), and forwards (FW, n = 2). The following inclusion criteria were defined: (i) starters included in each congested week (starter in one, two or three of the matches) participated in at least 50% of the matches as a starter and 90% of the training sessions during the previous three weeks; (ii) players were not injured or ill during the congested weeks or the three weeks before them; (iii) players were not injured for more than four consecutive weeks throughout the season.

Detailed information about the study design, procedures, and methodological approach was provided before the beginning of the study, and all players signed free consent before participating. The study followed the ethical standards of the Declaration of Helsinki and was approved by the scientific council of the local university.

### *External load monitoring*

An 18-Hz GPS unit (STATSports, Apex, Northern Ireland) was used for each player during the season. The GPS model was previously tested for its validity and reliability, revealing good levels of accuracy and variability at different speed thresholds (26) as well as excellent inter-unit reliability for peak velocity (27). Each player used the same unit during the full season in order to reduce the inter-variability level. The units were placed in a specific vest in which the unit was fixed between the scapulae. During the period of data collection, the range of satellites was 18 to 21. The data collected during training sessions and matches were imported and processed in the STATSport Apex software (version 5.0).

The following distance-based GPS variables were collected daily: (i) total distance (TD: consisting in the total distance covered by players; (ii) distance covered at high-intensity running (HIR: distance covered by the players at a speed of 14 $km \cdot h^{-1}$ or above); (iii) distance covered at high-speed running (HSR: distances covered at a speed of 19.8 $km \cdot h^{-1}$ or above); (iv) number of sprints ( ≥ 25.2 $km \cdot h^{-1}$) (NS: number of times that a speed of 25.2 $km \cdot h^{-1}$ or higher was achieved in running) (28). The volume (total per session and per match) of each measure was collected per player. Moreover, the acute load (wAL: weekly acute load), acute : chronic workload ratio (ACWL:

representing the division of wAL by the chronic load [the rolling average of accumulated training load in the previous 4 weeks]) (11), training monotony (TM: mean of training load during the seven days of the week divided by the standard deviation of the training load of the seven days), and training strain (TS: multiplication of wAL by the TM) were calculated by each distance-based measure following the original equation (12). Resulting from the calculus of these indices, each measure was coded as follows: aALTD (AL of TD); ACWRTD (ACWR of TD); TMTD (TM of TD); TSTD (TS of TD); aALHSR (AL of HSR); ACWRHSR (ACWR of HSR); TMHSR (TM of HSR); TSHSR (TS of HSR); aHIR (AL of HIR); ACWRHIR (ACWR of HIR); TMHIR (TM of HIR); TSHIR (TS of HIR); aALNS (AL of NS); ACWRNS (ACWR of NS); TMNS (TM of NS); and TSNS (TS of NS). All variables were calculated for each player in each week of the season.

**TABLE 3.** Descriptive and inferential statistics (mean ± SD) of total distance workload indices according to players' participation in matches.

| | S1M Mean ± SD | S2M Mean ± SD | S3M Mean ± SD | p | ES |
|---|---|---|---|---|---|
| aTD (m) | 40274 ± 13745 | 51048 ± 13018 | 52348 ± 9663 | S1Mvs.S2M: 0.010*<br>S1Mvs.S3M: 0.004*<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: -0.805 *moderate*¶<br>S1Mvs.S3M: -1.016 *moderate*¶<br>S2Mvs.S3M: -0.113 *trivial* |
| acwrTD (A.U.) | 1.0 ± 0.5 | 1.0 ± 0.2 | 0.9 ± 0.3 | S1Mvs.S2M: ≥ 0.999<br>S1Mvs.S3M: ≥ 0.999<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: < 0.001 *trivial*<br>S1Mvs.S3M: 0.242 *small*&<br>S2Mvs.S3M: 0.392 *small*& |
| mTD (A.U.) | 1.3 ± 0.4 | 1.2 ± 0.3 | 0.9 ± 0.2 | S1Mvs.S2M: 0.347<br>S1Mvs.S3M: 0.001*<br>S2Mvs.S3M: 0.023* | S1Mvs.S2M: 0.282 *small*&<br>S1Mvs.S3M: 1.264 *large*#<br>S2Mvs.S3M: 1.176 *moderate*¶ |
| sTD (A.U.) | 56235 ± 27376 | 60756 ± 25471 | 50307 ± 19394 | S1Mvs.S2M: ≥ 0.999<br>S1Mvs.S3M: ≥ 0.999<br>S2Mvs.S3M: 0.288 | S1Mvs.S2M: -0.171 *trivial*<br>S1Mvs.S3M:0.250 *small*&<br>S2Mvs.S3M: 0.462 *small*& |

aTD: weekly acute load of total distance; acwrTD: acute : chronic workload ratio of total distance; mTD: training monotony of total distance; sTD: training strain of total distance; S1M: starters in one match; S2M: starters in two matches; S3M: starters in three matches; *: p-value < 0.05; ES: effect size (standardized effect size of Cohen); &: small ES; ¶: moderate ES; #: large ES.

**TABLE 4.** Descriptive and inferential statistics (mean ± SD) of high-speed running distance workload indices according to players' participation in matches.

| | S1M Mean ± SD | S2M Mean ± SD | S3M Mean ± SD | p | ES |
|---|---|---|---|---|---|
| aHSR (m) | 1855 ± 855 | 3325 ± 990 | 2974 ± 1050 | S1Mvs.S2M: < 0.001*<br>S1Mvs.S3M: 0.001*<br>S2Mvs.S3M: 0.516 | S1Mvs.S2M: -1.589 *large*#<br>S1Mvs.S3M: -1.168 *moderate*¶<br>S2Mvs.S3M: 0.344 *small*& |
| acwrHSR (A.U.) | 0.9 ± 0.6 | 1.1 ± 0.4 | 1.0 ± 0.3 | S1Mvs.S2M: 0.369<br>S1Mvs.S3M: ≥ 0.999<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: -0.392 *small*&<br>S1Mvs.S3M: -0.210 *small*&<br>S2Mvs.S3M: 0.282 *small*& |
| mHSR (A.U.) | 0.7 ± 0.2 | 0.6 ± 0.2 | 0.6 ± 0.1 | S1Mvs.S2M: 0.783<br>S1Mvs.S3M: 0.051<br>S2Mvs.S3M: 0.372 | S1Mvs.S2M: 0.500 *small*&<br>S1Mvs.S3M: 0.632 *moderate*¶<br>S2Mvs.S3M: < 0.001 *trivial* |
| sHSR (A.U.) | 1246 ± 629 | 2122 ± 999 | 1662 ± 699 | S1Mvs.S2M: 0.002*<br>S1Mvs.S3M: 0.297<br>S2Mvs.S3M: 0.102 | S1Mvs.S2M: -1.049 *moderate*¶<br>S1Mvs.S3M: -0.626 *moderate*¶<br>S2Mvs.S3M: 0.533 *small*& |

aHSR: weekly acute load of high speed running distance; acwrHSR: acute : chronic workload ratio of high speed running distance; mHSR: training monotony of high speed running distance; sHSR: training strain of high speed running distance; S1M: starters in one match; S2M: starters in two matches; S3M: starters in three matches; *: p-value < 0.05; ES: effect size (standardized effect size of Cohen); &: small ES; ¶: moderate ES; #: large ES

*Statistical procedures*

Normality was assumed based on the central limit theorem. Descriptive statistics were presented in the form of mean and standard deviation in both tables and figures. The homogeneity of the sample was tested using the Levene test ($p > 0.05$). Comparisons of wAL, ACWL, TM and TS between starters in one, two or three matches were performed using repeated measures ANOVA followed by a Tukey post-hoc test. Descriptive statistics and inferential tests were performed in the SPSS software (version 25.0, IBM Corp., Armonk, USA) for a $p < 0.05$. Magnitude of differences was tested using the standardized effect size of Cohen (d) for a 95% confidence interval (95%CI), following the thresholds (29): 0.0;0.2, trivial; 0.2;0.6, small; 0.6;1.2, moderate; 1.2; 2.0, large; > 2.0, very large.

**TABLE 5.** Descriptive and inferential statistics (mean ± SD) of high-intensity running workload indices according to players' participation in matches.

| | S1M<br>Mean ± SD | S2M<br>Mean ± SD | S3M<br>Mean ± SD | p | ES |
|---|---|---|---|---|---|
| aHIR<br>(m) | 6587 ± 2883 | 10150 ± 3510 | 10969 ± 2785 | S1Mvs.S2M: 0.001*<br>S1Mvs.S3M: < 0.001*<br>S2Mvs.S3M: 0.944 | S1Mvs.S2M: -1.109 *moderate*¶<br>S1Mvs.S3M: -1.546 *large#*<br>S2Mvs.S3M: -0.258 *small* |
| acwrHIR<br>(A.U.) | 0.9 ± 0.5 | 1.0 ± 0.3 | 1.0 ± 0.3 | S1Mvs.S2M: 0.994<br>S1Mvs.S3M: 0.929<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: -0.242 *small*&<br>S1Mvs.S3M: -0.242 *small*&<br>S2Mvs.S3M: < 0.001 *trivial* |
| mHIR<br>(A.U.) | 0.7 ± 0.2 | 0.7 ± 0.2 | 0.7 ± 0.2 | S1Mvs.S2M: ≥ 0.999<br>S1Mvs.S3M: 0.290<br>S2Mvs.S3M: 0.492 | S1Mvs.S2M: < 0.001 *trivial*<br>S1Mvs.S3M: < 0.001 *trivial*<br>S2Mvs.S3M: < 0.001 *trivial* |
| sHIR<br>(A.U.) | 5124 ± 2470 | 7430 ± 3487 | 7111 ± 2482 | S1Mvs.S2M: 0.028*<br>S1Mvs.S3M: 0.084<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: -0.763 *moderate*¶<br>S1Mvs.S3M: -0.802 *moderate*¶<br>S2Mvs.S3M: 0.105 *trivial* |

aHIR: weekly acute load of distances covered at high-intensity running; acwrHIR: acute : chronic workload ratio of distances covered at high-intensity running; mHIR: training monotony of distances covered at high-intensity running; sHIR: training strain of distances covered at high-intensity running; S1M: starters in one match; S2M: starters in two matches; S3M: starters in three matches; *: p-value < 0.05; ES: effect size (standardized effect size of Cohen); &: small ES; ¶: moderate ES; #: large ES.

**TABLE 6.** Descriptive statistics (mean ± SD) of number of sprints workload indices.

| | S1M<br>Mean ± SD | S2M<br>Mean ± SD | S3M<br>Mean ± SD | p | ES |
|---|---|---|---|---|---|
| aNS<br>(n) | 23.5 ± 16.5 | 46.0 ± 20.3 | 39.8 ± 19.1 | S1Mvs.S2M: 0.000*<br>S1Mvs.S3M: 0.018*<br>S2Mvs.S3M: 0.641 | S1Mvs.S2M: -1.217 *large*¶<br>S1Mvs.S3M: -0.913 *moderate*¶<br>S2Mvs.S3M: 0.314 *small*& |
| acwrNS<br>(A.U.) | 0.9 ± 0.7 | 1.2 ± 0.6 | 1.1 ± 0.5 | S1Mvs.S2M: 0.363<br>S1Mvs.S3M: ≥ 0.999<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: -0.460 *small*&<br>S1Mvs.S3M: -0.342 *small*&<br>S2Mvs.S3M: 0.181 *trivial* |
| mNS<br>(A.U.) | 0.5 ± 0.2 | 0.5 ± 0.1 | 0.5 ± 0.1 | S1Mvs.S2M: ≥ 0.999<br>S1Mvs.S3M: 0.545<br>S2Mvs.S3M: ≥ 0.999 | S1Mvs.S2M: < 0.001 *trivial*<br>S1Mvs.S3M: < 0.001 *trivial*<br>S2Mvs.S3M: < 0.001 *trivial* |
| sNS<br>(A.U.) | 12.9 ± 9.4 | 25.7 ± 14.7 | 20.1 ± 10.3 | S1Mvs.S2M: 0.002*<br>S1Mvs.S3M: 0.162<br>S2Mvs.S3M: 0.237 | S1Mvs.S2M: -1.037 *moderate*¶<br>S1Mvs.S3M: 0.730 *moderate*¶<br>S2Mvs.S3M: 0.441 *small*& |

aNS: weekly acute load of number of sprints; acwrNS: acute : chronic workload ratio of number of sprints; mNS: training monotony of number of sprints; sNS: training strain of number of sprints; S1M: starters in one match; S2M: starters in two matches; S3M: starters in three matches; *: p-value < 0.05; ES: effect size (standardized effect size of Cohen); &: small ES; ¶: moderate ES; #: large ES

## RESULTS

Table 3 presents the differences between S1M, S2M and S3M for AL, ACWR, TM and TS for TD. The AL was significantly greater for S2M than S1M (27%; $p = 0.010$; $d = 0.805$, moderate ES) and was greater for S3M than for S1M (30%; $p = 0.004$; $d = 1.016$, moderate ES). TM was significantly greater for S1M than S3M (44%; $p = 0.001$; $d = 1.64$, large ES) and was greater for S2M than S3M (33%; $p = 0.023$; $d = 1.176$, moderate ES).

Table 4 presents the differences between S1M, S2M and S3M for AL, ACWR, TM and TS for HSR. The AL was significantly greater for S2M than for S1M (79%; $p < 0.001$; $d = 1.589$, large ES) and was greater for S3M than for S1M (60%; $p = 0.001$; $d = 1.168$, moderate ES). TS was significantly greater for S2M than for S1M (70%; $p = 0.002$; $d = 1.049$, moderate ES).

Table 5 presents the differences between S1M, S2M and S3M for AL, ACWR, TM and TS for HIR. The AL was significantly greater for S2M than for S1M (54%; $p = 0.001$; $d = 1.009$, moderate ES) and was greater for S3M than for S1M (67%; $p < 0.001$; $d = 1.546$, large ES). TS was significantly greater for S2M than for S1M (45%; $p = 0.028$; $d = 0.763$ moderate ES).

Table 6 presents the differences between S1M, S2M and S3M for AL, ACWR, TM and TS for NS. The AL was significantly greater for S2M than for S1M (96%; $p < 0.001$; $d = 1.217$, large ES) and was greater for S3M than for S1M (69%; $p = 0.018$; $d = 0.913$, moderate ES). TS was significantly greater for S2M than for S1M (99%; $p = 0.002$; $d = 1.037$, moderate ES).

## DISCUSSION

The purpose of this study was to analyse variations in the AL, ACWR, TM, and TS of distance-based GPS measures based on different levels of participation in matches (i.e., one, two, or three matches per week) among professional soccer players. The main finding was that the S2M and S3M had greater ALs than S1M for all distance-related variables, while no significant differences between S1M, S2M, and S3M were found for ACWR for any measure.

For all comparisons of TD, S3M had the greatest ALs. Also, S3M presented lower TM values than S2M and S1M, while no significant differences were found for TS or ACWR. In previous research, the overall distance measures were not affected in a congested period, revealing no significant differences between congested and non-congested weeks (30, 31). However, in the present study, congested weeks affected ALs for TD, mainly in S3M. This discrepancy between the present study and other studies may be related to the fact that they did not differentiate starters in different levels of participation, which could have masked any potential changes in players' workloads. Also, lower TM values in S3M were expected, as the training sessions between matches in congested weeks are limited and have lower volumes (32, 33). This can provide new information about players who are exposed to high acute loads of TD and allow coaches to adjust training sessions in accordance with recovery strategies.

Considering HSR distances, the S2M presented the greatest AL and TS values, though no significant differences were found for ACWR or TM values. Our results are in contrast with a study conducted in 32 elite soccer players, which found that despite the increased injury rate during a congested week, distance-based measures such as HSR were not affected (34). This suggests that increased fatigue indices after a congested period might not be related to distance-based metrics. Instead, fatigue might be related to mechanical work (e.g., accelerations, decelerations, impacts, and high metabolic distances) (35). High ALs of HSR combined with high ACWR values are associated with a high risk of injury (36). Although the ALs of HSR presented in the present study are higher than the values found in a regular week of training (37), the ACWR remained within the values of 0.9 and 1.3 A.U. (recommended interval to avoid a significant increase in injury risk (11)), suggesting that the ALs of HSR might not be harmful to S2M and S3M (38).

Our results showed that S2M and S3M had significantly greater ALs and TS values than S1M for distances covered at HIR, but no significant differences were found for ACWR and TM. Although there is some inconsistency among previous studies regarding the nomenclature used for different speed zones (7), several studies have used our speed thresholds for distances covered at HIR (33, 39, 40). In line with our results, a previous study found that weekly accumulated ALs for HIR were significantly greater in congested weeks than in regular weeks (33). However, the authors did not differentiate starters in different levels of participation. In contrast, in a study conducted on 42 elite soccer players from the Spanish League, it was found that HIR was not affected by congested fixture periods (40). Despite the lack of statistically significant differences found in that study, it was suggested that the changes observed can influence match outputs. This is in line with our results that revealed no statistically significant differences between S1M and S3M for TS values; however, a moderate effect size was found for the difference in running speed.

Regarding the number of sprints, S2M and S3M showed higher AL and TS values than S1M, whereas no significant differences were found for ACWR and TM. Similarly to our results, other researchers found that cumulative loads of sprints increased during congested weeks (33). However, in that study (33), differences with a large effect size were found only between regular weeks and congested weeks with three matches; small differences were found between normal weeks and weeks with two matches, which contrasts with our results.

Some studies concerning distance measures during congested periods (31, 39) are in contrast with the trend of an increased number of sprints between weeks found in this study. Therefore, attention should be paid to decreases in high-intensity efforts caused by temporary fatigue levels, which may result in a higher risk of hamstring injuries (41, 42). Also, the shorter recovery periods between matches in congested weeks could be harmful to players if the changes in load found in the present study are not considered and adjustments to training loads are not made accordingly. The potential changes in this metric should not be ignored, as doing so could increase the risk of injury to players' lower limbs.

The lack of ACWR differences in our study for the overall distance measures suggests that even during a congested period, players can experience greater (or equivalent) chronic loads in relation to ALs. This allows them to cope with the demands of a congested week and to be aware that an ACWR of ~1.2 to 1.6 A.U. for TD may be associated with a higher risk of injury (11). Also, the lack of TM differences and low values found in this study suggest that despite the participation in two to three matches in a week, there is great variation in distance metrics. This might be related to the combination of "hard days" and "easy days" between matches, resulting in reduced TM and TS (12). However, significant differences were found for TS values for the majority measures, which can be attributed to coaches' tactical strategies during congested periods, such as player rotations (15).

This study was the first, to the best of our knowledge, to analyse the effects of congested weeks on ALs, ACWR, TM, and TS of distance-based measures according to players' participation in matches. Nonetheless, our study has some limitations. The main limitation was related to the sample size. In fact, only one team was analysed, which may influence the final analysis of the patterns observed. Therefore, future studies should corroborate our findings. Also, it would be interesting to investigate the effect of congested fixtures on ACWR, TM, and TS through accelerometry-based or internal measures of S1M, S2M, and S3M over a full season.

Considering the evidence discussed above, coaches and practitioners should consider analysing the changes in different distance metrics between S1M, S2M, and S3M, as a way to properly manage the impact of these periods on players and adjust training and recovery strategies based on the type of participation in matches. Additionally, considering the significantly lower AL of S1M comparing to those who played 2 and 3 matches as starters, it would be interesting to prescribe a supplementary, individually and adjusted work (e.g., high-intensity interval training) to level the load of those who have played less to those who played more (43).

## CONCLUSIONS

The current study revealed that weekly acute load significantly increases in players who participate more in matches. This may suggest that coaches should pay special attention to players who do not participate in matches to provide similar loads in training sessions aiming to promote balance in the exposure to acute loads. Additionally, it can be recommended to coaches that they organize recovery strategies for players who play most and, naturally, prepare previous weeks in accordance with expectable values of acute load during congested ones.

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