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A New Approach for Training-load Quantification in Elite-level Soccer: Contextual Factors

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ABSTRACT

The aims of this study were to analyse the physical responses of professional soccer players during training considering the contextual factors of match location, season period, and quality of the opposition; and to establish prediction models of physical responses during training sessions. Training data was obtained from 30 professional soccer players from Spanish La Liga using global positioning technology (N = 1365 performances). A decreased workload was showed during training weeks prior to home matches, showing large effects in power events, equivalent distance, total distance, walk distance and low-speed running distance. Also, the quality of the opposition also affected the training workload ($p < 0.05$). All regression-models showed moderate effects, with an adjusted R2 of 0.37 for metabolic-work, 0.34 for total distance covered, 0.25 for high-speed running distance (18–21 $km \cdot h^{-1}$), 0.29 for very high-speed running distance (21–24 $km \cdot h^{-1}$), 0.22 for sprint running distance (> 24 $km \cdot h^{-1}$) and 0.34 for equivalent distance. The main finding of this study was the great association of match location, season period and quality of opposition on the workload performed by players in the training week before the match; and the development of workload prediction-models considering these contextual factors, thus proposing a new and innovative approach to quantify the workload in soccer.

Introduction

Nowadays winning is the most important aspect in high-level soccer [1]. Despite many factors (technical, tactical, physical or physiological, among others) affect the performance of players [2], performance is currently assessed through victory or defeat. It is known that players require a multi-faceted ability that responds to the game needs [3]. In an increasingly demanding sport, where teams compete up to twice a week for a long period, players require a good readiness to withstand the match demands over the season and avoid increasing the risk of injury [4, 5]. Therefore, developing an appropriate load periodization and programming is of paramount importance in a high-level. Global Positioning Systems (GPS) have been shown to be a valid and reliable tool to monitor the external load of elite soccer players in both training and matches [6–8]. These devices provide detailed information relative to the locomotion activity performed by players such as time-motion or metabolic metrics. The analysis of locomotion activity based on speed-running (e. g., high-intensity distance, number of accelerations or sprint distance) is the most used method to monitor external load in soccer [9, 10]. However, an increasing number of authors currently support the metabolic approach based on the energy cost (e. g. metabolic power, equivalent distance or metabolic power events) as a more accurate method for workload monitoring due to it considers the energy cost associated with accelerative and decelerative phases during the soccer-specific activities [6, 11].

High-level soccer has evolved in recent years requiring better physical, technical and tactical preparation of players to withstand the increased competition demands [4, 5]. Therefore, practitioners must take into account a wide myriad of factors that may affect the physical performance of players in order to improve the training program and achieve a better readiness for the match. In this sense, many studies have shown the contextual factors such as match location [12, 13], quality of opposition [12, 14, 15] or season period [13, 14] greatly affect the players' physical responses in match and, consequently, in match outcome. These authors found that home teams covered longer total distance and the best teams showed higher ball possession. In addition, regardless of the quality of opposition and the match location, an increased total distance and high-intensity distance were covered in the last period of the season. Finally, different physical responses were found according to playing position [16–19].

However, most of the authors have analysed the effect of contextual factors on players' physical responses in competition [20–24], and only a few authors have analysed how contextual factors affect the physical performance in training sessions [25, 26]. These authors found a significant affectation of contextual factors on the workload applied on the training week after the match and consider that taking into account the contextual factors on the training week just before the match would of great practical application for practitioners to make decisions on the training load (TL) programming.

Knowing that away matches or playing against a top-quality team the physical responses developed by players in the match are higher than when the match is at home [12, 13] or playing against a lower quality team [12, 14, 15], the authors hypothesized that when the match is against a top-quality team or when playing away, the physical responses performed by players on the training days (TDs) just before the match will be also higher in order to simulate the upcoming-match demands. On the other hand, contrary to other authors who found higher physical responses on the last period of the season [13, 14], the authors also believe that TL will be higher during the initial period of the competitive season because players are still 'fresh' and might continue their initial physical preparation from preseason. Therefore, there is a double object of study; (1) to analyse the effect of match location, season period and quality of opposition on the physical responses of professional soccer players in the training week prior to the match; and (2) to establish predictive models of several physical metrics in training considering the effect of contextual factors.

Materials and Methods

Participants and sample

Training data was collected from 30 male professional soccer players (22.8 ± 0.8 yr; 177.8 ± 6.9 cm; 73.3 ± 5.7 kg) belonging to a Spanish First Division team during the 2015–2016 season ($N = 1365$ cases). Only the data corresponding to team training sessions performed on the field during the competitive period was used. The records obtained during preseason and non-competition period (corresponding to Christmas), in addition to purely tactical and strength sessions realized at the gym have also been excluded to avoid variability in the training records. The Competitive Period began in microcycle 8, corresponding to the second match-week. Thus, a total of 33 training weeks were included.

Players were classified into five playing positions [16, 17, 27]: Central Defender (CD), External Defender (ED), Central Midfielder (CM), Wide Midfielder (WM) and Forward (FO). Goalkeepers and players who did not complete the entire training session were also excluded from the analysis. Training sessions were divided according to the TD relative to the match-day (MD): 4 days before the match (MD-4), 3 days before the match (MD-3), 2 days before the match (MD-2) and 1 day before the match (MD-1). Training sessions developed before MD-4 are usually orientated to recovery [28, 29] and were not considered for analysis as do not present any specific and representative content by position. Punctual microcycles with two weekly matches and exclusively tactical training sessions were discarded from the study.

The Club and players were informed about the aim of this study, and consent was obtained by both. This study was approved by the University of Granada Ethics Committee (Number 471/CEIH/2018). It complied with the ethical standards of the Journal [30] and followed the guidelines of the Declaration of Helsinki (2013).

Data collection procedures and variables analysed

Global Positioning System devices (GPS) of 18.18 Hz (GPEXE Pro®, GPEXE, Udine, Italy) were used to collect data for this study for all training sessions. The number of satellites during the training and matches was 8 ± 1.

Time-motion parameters and metabolic variables were analysed. The time-motion parameters are as follows: acceleration events (ACC), considered as the number of speed increments equal to or greater than $2\,m \cdot s^{-2}$ during an interval time equal to or less than 0.5 s; deceleration events (DEC), considered as the number of braking or speed decrements equal to or less than $-2\,m \cdot s^{-2}$ during an interval time equal to or less than 0.5 s; total distance covered during the match (TotalD); low-speed running distance (LSRD), i. e., the distance covered at speeds $<14\,km \cdot h^{-1}$; medium-speed running distance (MSRD), from 14 to $18\,km \cdot h^{-1}$; high-speed running distance (HSRD), from 18 to $21\,km \cdot h^{-1}$; very-high-speed running distance (VHSRD), from 21 to $24\,km \cdot h^{-1}$; and sprint running distance (SPD), higher than $24\,km \cdot h^{-1}$. All evaluated distances were recorded in meters. The variables belonging to the metabolic approach analysed in this study are as follows: average metabolic power (MP); metabolic work (MW, in kJ), which was calculated as the product of average metabolic power and training duration in seconds; mean metabolic power of high-intensity actions (MPev, on $W \cdot kg^{-1}$), which considers the actions with intensities equal to or greater than $20\,W \cdot kg^{-1}$; number of high-intensity events (PowerE); and the equivalent distance (EqD, in meters), based on the distance that the player would have covered at a steady pace, using the total energy consumed over the match [11, 31].

Relative to contextual factors, training and match data were classified according to the season period; from August to November (Start), December to February (Middle) and March to May (Final) [5, 13, 14]; and considering the quality of the opposition; differentiating the teams in three levels according to their League ranking at the end of the previous match-week [25]: 'Top-teams' (1st to 6th), 'Medium teams' (7st to 14th) and 'Weak teams' (15st to 20th). Only the TDs prior to a League match have been included, excluding the TDs before a Cup match or the weeks without competition.

Statistical analysis

Microsoft Excel 2019 (Microsoft Corp, Redmond, Washington, USA), SPSS (version 25.0; SPSS Inc., Chicago) and R Studio (version 3.6.1; R Core Team, 2019) were used for data processing and statistical analyses. For all analyses, the level of significance was set at $p \leq 0.05$ and the results have been described as means ± SD. First, the Kolmogorov-Smirnov test was performed to know if dependent variables had a normalized distribution. The results showed that these variables did not present a normalized distribution. However, due to the large sample size of each group, the central limit theorem was applied to provide normally distributed sample means [32]. Therefore, the parametric analyses were performed in this study. The relationships between dependent variables and contextual factors were determined using multiple bivariate correlations, represented by Pearson's coefficient. The magnitude of the correlation was interpreted as follows: < 0.1, trivial; from 0.1 to 0.3, small; from 0.3 to 0.5, moderate; from 0.5 to 0.7, large; from 0.7 to 0.9, very large; and from 0.9 to 1.0, almost perfect [33]. To compare the TL between groups considering the match location (home or away), independent-sample T-tests were performed. ANOVA and Bonferroni post hoc tests, with quality of opposition (weak, medium or top teams) as factor, were conducted in order to know the differences among TL' variables between the quality of teams and season period. Subsequently, Cohen's *d* (for T-test analyses) and Eta-squared (η^2, for ANOVA test) were used to quantify the effect size (ES) for interpreting the differences that were found between groups [34, 35]. The threshold values for Cohen's *d* are: < 0.2 for trivial effect, 0.2 to 0.5 for small effect, 0.5 to 0.8 for moderate effect, and > 0.8, for large effect [34]. The values of ES for η^2 are 0.02 for small effects, 0.15 for moderate effects and 0.35 for large effects. Finally, in order to examine the effect of the different contextual factors on the TL, different regression models were fit for the different dependent variables. These variables were MW, TotalD, HSRD, VHSRD, SPD, and EqD, resulting in six regression models. The independent variables used were the same for all models, i. e. season period, number of days before the MD, the position of the respective player, location of the upcoming match and the quality of opposition. All independent variables were coded as categorical variables. The fit and overall significance of the respective models were estimated using the determination coefficient R-squared (R^2) and the significance of the respective predictors was checked using Wald t-tests.

Results

▶ **Table 1** shows the relationship between contextual factors and TL parameters determined by Pearson's coefficient test. Several significant correlations ($p \leq 0.05$ and $p \leq 0.01$) were found between the physical responses and the contextual factors, being the match location, which presented a higher number of correlations. The correlations showed trivial and small effects.

▶ **Table 1** Pearson's coefficient test of physical responses and contextual factors.

Variable	MP	MPev	PowerE	ACC	DEC	EqD	TotalD	WalkD	LSRD	MSRD	HSRD	VHSRD	SPD
SeasonP	−0.078**	−0.050	−0.007	0.057*	0.041	−0.033	−0.043	−0.022	−0.004	−0.064*	−0.163**	−0.196**	−0.110**
Location	0.099**	0.068**	0.145**	0.143**	0.113**	0.135**	0.132**	0.173**	0.155**	−0.011	0.110**	0.135**	0.002
RQ	−0.021	0.067**	0.055*	0.048	0.084**	0.051*	0.048	0.046	0.048	0.019	0.013	0.017	0.103**

* ($p \leq 0.05$), ** ($p \leq 0.01$); SeasonP, season period; MO, Match outcome; RQ, rival-team quality; MP, averaged Metabolic Power on $W \cdot kg^{-1}$; MPev, mean metabolic power of high-intensity actions on $W \cdot kg^{-1}$; PowerE, number of high-intensity events ($\geq 20\,W \cdot kg^{-1}$); ACC, acceleration events; DEC, deceleration events; EqD, Equivalent Distance on meters; TotalD, total distance covered on meters; WalkD, total walking distance covered (0 to $7\,km \cdot h^{-1}$); LSRD, low-speed running distance ($< 14\,km \cdot h^{-1}$); MSRD, medium-speed running distance (14 to $18\,km \cdot h^{-1}$); HSRD, high-speed running distance (18 to $21\,km \cdot h^{-1}$); VHSRD, very high-speed running distance (21 to $24\,km \cdot h^{-1}$); SPD ($> 24\,km \cdot h^{-1}$).

Match location

The independent-samples T-test concerning to the match location showed higher workload values on training-weeks when the team played an away-match compared to training-weeks before a home-match. Except for MSRD and SPD, all the parameters analysed were significant for $p < 0.01$ (▶ **Table 2**). PowerE, EqD, TotalD, WalkD and LSRD showed large effects ($d = 0.47$, 0.52, 0.50, 0.60 and 0.58, respectively).

Quality of opposition

ANOVA with Bonferroni's post hoc tests were carried out to compare the TL between top-, medium-, and weak quality teams: in MPev, the medium-quality teams showed different values than weak ($p < 0.01$) and top teams ($p < 0.001$), and weak teams differed from top teams ($p < 0.05$); in the variable DEC, weak teams differed from medium ($p < 0.01$) and top teams ($p < 0.001$); in EqD, the weak teams showed variability compared to medium ($p < 0.001$) and top teams ($p < 0.001$); in TotalD, weak teams differed from medium ($p < 0.05$) and top teams ($p < 0.01$); in LSRD, weak differed again from medium ($p < 0.01$) and top teams ($p < 0.001$); for the metric MSRD, medium differed from weak ($p < 0.001$) and top teams ($p < 0.05$); for VHSRD, the workload applied by medium teams was different than weak ($p < 0.001$) and top teams ($p < 0.001$); and finally in SPD, top teams differed from weak ($p < 0.001$) and medium teams ($p < 0.001$).

Season period

The regression model coefficients showed a decrease in all training load variables from the start to the middle period of the season and a further decrease from the middle to the end of the season. In all regression models of physical metrics, both the coefficients for start- and middle period showed significant results in the Wald t-tests ($p < 0.001$), corroborating the reliability of the estimations.

Prediction models

The equations for the six models are shown in ▶ **Table 3**. All models showed overall significant effects ($p < 0.001$). The models for MW yielded an adjusted R^2 value of 0.37; TotalD = 0.34; HSRD = 0.25; VHSRD = 0.29; SPD = 0.22 and EqD = 0.34. The predictions made by the model, i. e. the mean values of the respective load variables depending on the different independent variables are shown in ▶ **Fig. 1**.

Discussion

The main goal of this study was to analyse and compare the TL in elite soccer players considering different contextual factors and develop prediction models of physical metrics from the different factors considered. The results showed differences in the TL performed by players among microcycles depending on the quality of opposition and the location of the upcoming match. However, the main finding of this study was the significant effects found in all regression-models, thus proposing a new and innovative approach for training load quantification and planning, taking into account the different contextual factors.

It is well known that contextual factors such as location or quality of opposition highly affect the physical responses of players in a match [20, 26, 36]. Indeed, Lago-Peñas [20] concluded that these situational variables should be considered for the post-match analysis of physical performance. However, there is scarce research analysing how contextual factors affect physical performance in training. The results of the present study showed significant correlations between contextual factors and the different physical responses in training, and the match location was the factor with the greatest influence on physical responses. In this sense, many authors agree that home teams cover higher low-speed distance in competition [12, 13]. However, these authors did not find significant differences at maximum or sub-maximum intensities. On the other hand, some authors analysed how the match location affects the workload performed by players in the training-week. Rago et al. [26] found a lower number of accelerations and decelerations events on the week after playing away, and Brito et al. [25] showed higher TL after playing away. The present study found several variances among metrics, showing higher values in all physical responses on the training-week when the upcoming match took place away com-

▶ **Table 2** Descriptive data (mean ± SD), Cohen's *d* and effect size (ES) interpretation of variables with significant variance between them, considering the match location (home or away) of the upcoming match.

Variable	Home (N = 722)	Away (N = 643)	*p*	*d*	*ES*
MP	6.4 ± 1.1	6.7 ± 1.1	***	0.27	*Mod*
MPev	28.2 ± 2.0	28.6 ± 1.7	**	0.17	*Small*
PowerE	69.1 ± 24.4	81.3 ± 27.6	***	0.47	*Large*
ACC	37.7 ± 15.6	43.6 ± 15.9	***	0.37	*Mod*
DEC	35.8 ± 15.5	41.4 ± 16.2	***	0.35	*Mod*
EqD	4515.6 ± 1303.7	5212.7 ± 1389.2	***	0.52	*Large*
TotalD	4025.2 ± 1188.2	4633.3 ± 1242.8	***	0.50	*Large*
WalkD	2037.9 ± 547.2	2370.0 ± 569.1	***	0.60	*Large*
LSRD	3275.4 ± 941.1	3837.3 ± 1006.2	***	0.58	*Large*
HSRD	152.4 ± 126.9	185.2 ± 102.3	***	0.28	*Mod*
VHSRD	69.0 ± 59.2	93.1 ± 80.7	***	0.34	*Mod*

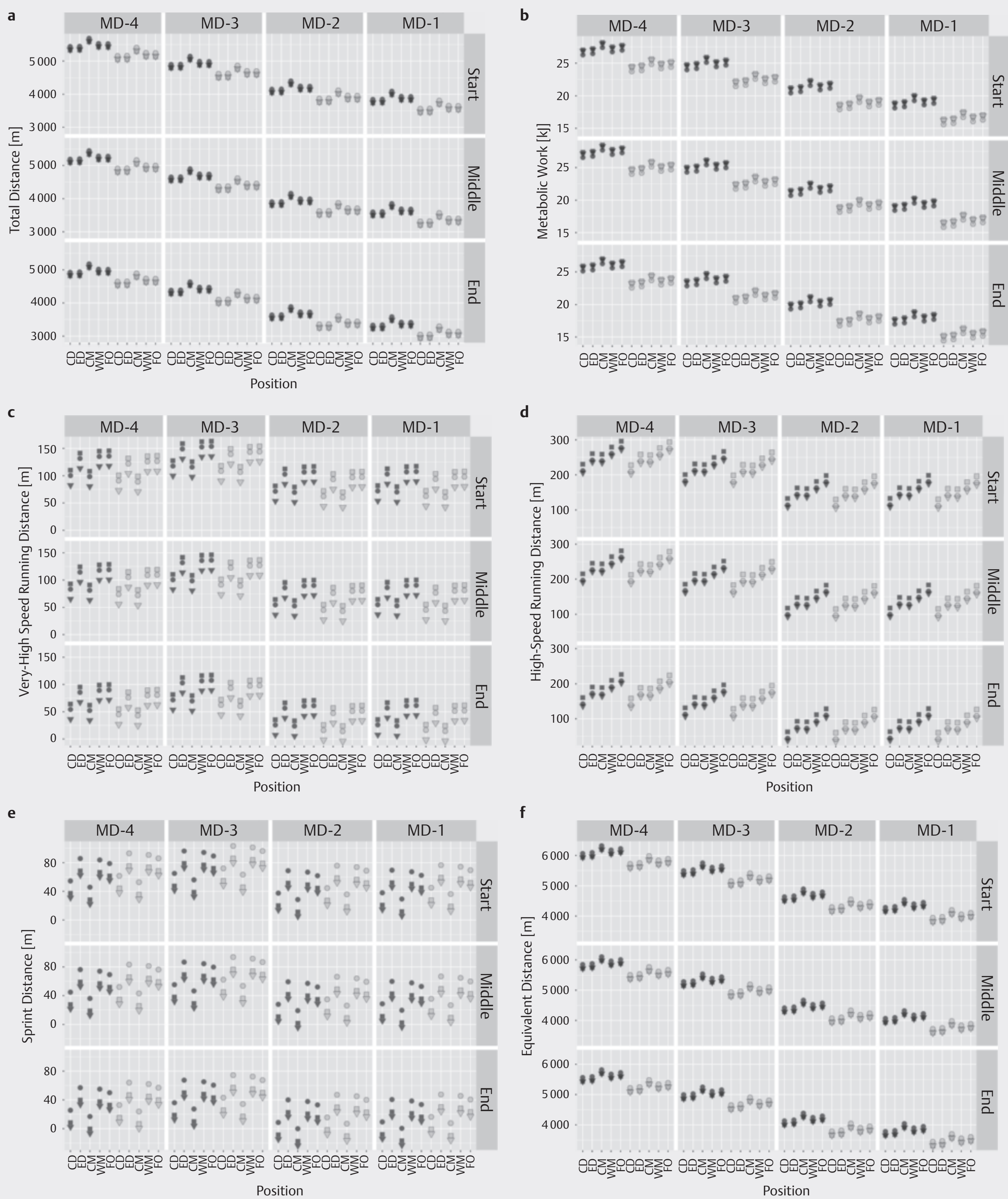
($p \leq 0.05$)*; ($p \leq 0.01$)**; ($p \leq 0.001$)***. MP, averaged Metabolic Power on $W \cdot kg^{-1}$; MPev, mean metabolic power of high-intensity actions on $W \cdot kg^{-1}$; PowerE, number of high-intensity events ($\geq 20\, W \cdot kg^{-1}$); ACC, acceleration events; DEC, deceleration events; EqD, Equivalent Distance on meters; TotalD, total distance covered on meters; WalkD, total walking distance covered (0 to $7\, km \cdot h^{-1}$); LSRD, low-speed running distance ($< 14\, km \cdot h^{-1}$); HSRD, high-speed running distance (18 to $21\, km \cdot h^{-1}$); VHSRD, very high-speed running distance (21 to $24\, km \cdot h^{-1}$).

▶ **Table 3** Coefficients for the models of the different load parameters (columns) and the respective independent variables (rows). SeasonP, season period; MD, match day; Pos, playing position; Loc, match location; RQ, rival-team quality; Med, medium.

	Equation
Model 1	MW = 17.77 + (x * Season) + (y * MD) + (z * Pos) + (a * Loc) + (b * RQ)
	x: SeasonP: Final: 1; SeasonP: Middle = 1.42; SeasonP: Start = 1.13; y: MD-1 = 1; MD-2 = 2.31; MD-3 = 5.88; MD-4 = 8.15 z: CD = 1; CM = 1.13; ED = 0.19; FO = 0.71; WM = 0.47. a: Home = −2.55; Away = 1. b: Low teams = 1; Med teams = −0.16; Top teams = −0.78.
Model 2	TotalD = 3220.7 + (x * Season) + (y * MD) + (z * Pos) + (a * Loc) + (b * RQ)
	x: SeasonP: Final: 1; SeasonP: Middle = 265.9; SeasonP: Start = 513.1; y: MD-1 = 1; MD-2 = 307.8; MD-3 = 1054.3; MD-4 = 1597.8 z: CD = 1; CM = 251.13; ED = 6.74; FO = 86.01; WM = 91.4. a: Home = −282.65; Away = 1. b: Low teams = 1; Med teams = 18.39; Top teams = 108.84.
Model 3	HSRD = 63.19 + (x * Season) + (y * MD) + (z * Pos) + (a * Loc) + (b * RQ)
	x: SeasonP: Final: 1; SeasonP: Middle = 55.03; SeasonP: Start = 69.84; y: MD-1 = 1; MD-2 = −0.45; MD-3 = 67.89; MD-4 = 97.28 z: CD = 1; CM = 28.48; ED = 30.23; FO = 65.72; WM = 48.9. a: Home = −2.31; Away = 1. b: Low teams = 1; Med teams = −24.23; Top teams = −18.17.
Model 4	VHSRD = 35.79 + (x * Season) + (y * MD) + (z * Pos) + (a * Loc) + (b * RQ)
	x: SeasonP: Final: 1; SeasonP: Middle = 28.96; SeasonP: Start = 45.93; y: MD-1 = 1; MD-2 = −0.37; MD-3 = 45.83; MD-4 = 28.4 z: CD = 1; CM = −1.97; ED = 31.13; FO = 35.58; WM = 34.82. a: Home = −9.41; Away = 1. b: Low teams = 1; Med teams = −27.84; Top teams = −9.81.
Model 5	SPD = −8.04 + (x * Season) + (y * MD) + (z * Pos) + (a * Loc) + (b * RQ)
	x: SeasonP: Final: 1; SeasonP: Middle = 19.17; SeasonP: Start = 28.77; y: MD-1 = 1; MD-2 = −0.61; MD-3 = 26.82; MD-4 = 16.41 z: CD = 1; CM = −8.82; ED = 31.29; FO = 24.29; WM = 29.2. a: Home = 7.05; Away = 1. b: Low teams = 1; Med teams = −6.07; Top teams = 17.32.
Model 6	EqD = 3655.08 + (x * Season) + (y * MD) + (z * Pos) + (a * Loc) + (b * RQ)
	x: SeasonP: Final: 1; SeasonP: Middle = 283.04; SeasonP: Start = 502.99; y: MD-1 = 1; MD-2 = 348.24; MD-3 = 1209.94; MD-4 = 1779.58 z: CD = 1; CM = 256.68; ED = 28.87; FO = 161.75; WM = 114.04. a: Home = −341.16; Away = 1. b: Low teams = 1; Med teams = 1.32; Top teams = 127.65.

pared to playing at home. Conversely, Brito et al. [25] found a higher RPE (rate of perception effort) when preparing for a home match. However, it should be noted that the present study analysed the effect of match location on the locomotion activity in the training week just before the match, whereas Rago et al. [26] analysed the effect over the following week and Brito et al. [25] considered the internal load (RPE). Relative to the season period, some authors have suggested a monotony in training methods in professional soccer due to the similar TL found over the season [27]. Other studies have shown the highest total distance and high-intensity distance in the final period [13, 14]. Conversely, these results showed higher physical responses at the beginning of the season compared to the rest of the season, whereas load also tended to be a little higher in the middle period compared to the end of the season. It may be due to players were exhausted at the end of the season, so the TL was adjusted either consciously by coaches or unconsciously by players. Therefore, there is controversy in the research regarding to the season period.

The quality of opposition is one of the most determinant factors on the physical performance developed by players [15, 20, 37]. In a match, playing against the best teams requires a greater physical effort, and these efforts are usually made without the ball in the attempt to regain possession. Thus, it may be adequate to consider the quality of the next rival for programming the weekly TL in order to achieve a more specific preparation and peak performance on a match. Although the authors do not know if the technical staff considered this factor for TL programming, this study found variability on the TL depending on whether the team played against top, medium or weak teams. In line with Brito et al. [25], the results showed higher TL during the training-week when the team played against top-teams. Contrary to this study, Rago et al. [26] found higher TotalD, ACC and DEC on the week before the match when played against weak teams. Therefore, this study suggests that the quality of opposition should be considered for TL periodization due to the effect on physical performance. On the other hand, it might also be interesting to take into account the quality of the opponent to carry out a tapering strategy for future matches [17]. For in-



▶ **Fig. 1** Predictions of regression models for Total Distance **a**, metabolic work **b**, high-speed running distance **c**, very high-speed running distance **d**, sprint running distance **e** and equivalent distance **f**; depending on the five independent variables. The analysed metrics are shown on Y-axis, and playing position on X-axis. The factors season period and number of days before the match are shown by splitting the data into grids. Besides, the colour of points indicates the location of the upcoming match, dark colour for away match and light colour for home matches; and the shape of points indicates the quality of the opponent; squares for bottom teams, triangles for medium teams and circles for top teams.

stance, if the analysed team is on the bottom of the ranking-table and the next match is against one of the best teams, but the 3 following matches are against direct rivals (i. e., similar ranking), it may be more adequate to periodize the TL in order to determine peak performance on these matches.

As discussed above, contextual factors also affect the players' physical performance during the training-week before the match. However, for the knowledge of authors, it is unknown how practitioners could take into account the specific influence of these factors on the workload planning during the training sessions before the match. To consider the effect of contextual factors on TL quantification, prediction models of running-distances and MW metrics have been developed. The regression analyses showed similar trends for most of the load parameters, but some differences were found. The largest TL changes were induced by training-day, i. e. the number of days between training-session and the upcoming match. However, no large differences were showed between MD-2 and MD-1. In the same line, other authors have found a greater load reduction on MD-2 and MD-1 compared to other TDs [17]. For these authors, it may be due to the tapering strategy of microcycle and the specific physical contents developed, focused on the reduction of TL by the proximity of match. Besides, these authors also considered necessary to contextualize each TD to different goals: MD-2 was oriented to train technical skills and tactics whilst MD-1 was oriented to low-intensity activation exercises and set pieces. Interestingly, in this study the metrics TotalD, EqD, MW and HSRD were reduced linearly with every training session, while VHSRD and SPD were first increased from MD-4 to MD-3 to be drastically reduced towards MD-2 and to be slightly increased again to MD-1, giving insight into an important aspect of periodization. While TotalD and high-speed running distances, as well as metabolic parameters, may all be used to quantify load characteristics, they may not reflect the same 'type' of load. Especially VHSRD and SPD did not follow the same trends as the remaining variables. Therefore, VHSRD and SPD might be intensity-related metrics, whereas the others (TotalD, EqD, MW and HSRD) may be volume-related.

Although it has been proposed a new perspective for load analysis considering the contextual factors, this study presents certain limitations. The results obtained belong to a single team. Moreover, technical-tactical factors such as playing style have not been considered in the analysis. On the other hand, it is likely the factor quality of opposition may affect differently if the analysed team play against a team is under- or over-ranked. For instance, the analysed team ranking bottom positions and playing against a top-tier team, or if both teams are in the same tier. In addition, it is likely different playing against top- or bottom-tier team if the referred team is ranked at the top, medium or bottom table. However, to build the prediction models the authors did not consider this approach because it wanted to know the effect of the quality of opposition, and not according to the difference in the ranking between teams. So, the authors wanted to prevent 'similar results' when playing against equal-tier teams but at the top or bottom. Besides, this paper considers the quality of opposition in the same way that others authors [20, 25, 26]. Finally, only the TL has been analysed. In this sense, future lines of research should focus on analysing the TL together with the match demands, collecting a greater number of teams, considering the technical-tactical elements, and analysing the physical performance fluctuations when playing against similar, lower or higher ranking-tier.

Conclusions

Two important conclusions can be drawn from this study. First, insights on the periodization of a high-level soccer team depending on contextual factors can be made. Second, two different categories of TL parameters may be identified; on the one hand, TotalD, HSRD, EqD, and MW might be termed volume-related load parameters; on the other hand, SPD and VHSRD, which could be termed intensity-related load parameters. Practitioners must take into account this distinction when reporting about the team's workload. Other interesting findings are that situational variables as match location or the quality of opposition alter the TL developed by players. The players showed higher TL within the training-week when the upcoming match was away and against a top opponent. However, consideration should be given to possible tapering strategies by the team. It does not know if it might either be that there is a conscious reason for this planning or that an unconscious and unwanted alteration in TL was identified. Either way, further studies should try to identify why contextual factors may alter the TL and how the training load interacts with training contents.

Practical Applications

It is known that contextual factors significantly alter the performance of players. However, most studies have only analysed the match load. This study proposes a new and innovative approach for TL quantification through TL prediction-models considering different contextual factors that might be useful in the soccer practice. These equations might be very useful for coaches to improve the TL periodization and programming 'predicting' the TL that players should develop on the different TDs by playing position considering the effect of the season period, match location and quality of opposition. Therefore, these models predict the recommended TL in order to achieve the best readiness considering the upcoming 'match scenario'. Furthermore, for the upcoming 'match scenario', coaches and staff can program the load based on these recommendations. In addition, it is recommended to discriminate between volume- and intensity- related variables into the load periodization in soccer.

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Conflict of Interest

The authors declare that they have no conflict of interest.

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