ORIGINAL ARTICLE

TRENDS in
Sport Sciences
2025; 32(2): 99-106
ISSN 2299-9590
DOI: 10.23829/TSS.2025.32.2-6

Impact of maximal sprinting speed on very high-speed running distance, sprinting distance and peak sprinting speed during soccer matches

LEONIDAS PAPADAKIS[1], IOANNIS ISPYRLIDIS[1], KONSTANTINOS PATRAS[2]

Abstract

Introduction. **Player on-field performance is often dictated by tactical constraints such as positional demands, playing formation and match scoreline. However, the relationship between how fast players run during an actual match compared to how fast they are able to run under controlled testing conditions is not well established.** Aim of Study. **The present study sought to investigate the effect of maximal sprinting speed (MSS) on match very high-speed running distance (VHSR), sprinting distance (SpD) and peak sprinting speed (PSS) in professional football players.** Material and Methods. **Sixteen players were monitored though an entire in-season phase (26 matches, n = 170 individual observations). Global positioning system samplings at 10 Hz were used to measure VHSR, SpD and PSS. MSS was recorded as the highest speed achieved throughout the season during top-speed training sessions and/or large-sided games. Linear mixed effects model was used to quantify the effect of MSS after adjusting for seasonal trends of the response variables as well as the within-player, between-player and between-game sources of variability. Effects were evaluated using non-clinical magnitude-based decisions.** Results. **Our results indicated that faster players covered on average very likely substantially more SpD (48.2 m [90% CI: 26.0 to 70.2], 41.0% [90% CI: 15.1 to 72.1]), and reached on average very likely substantially higher PSS than their slower counterparts (1.1 km·h^{-1} [90% CI: 0.8 to 1.4], 3.6% [90% CI: 2.5 to 4.6]). In addition, PSS showed on average a very likely substantial seasonal reduction (–1.2 km·h^{-1} [90% CI: –1.9 to –0.4], –3.7% [90% CI: –5.9 to –1.4]).** Conclusions. **Higher MSS is beneficial for SpD and PSS in professional soccer players; however, substantial seasonal reductions in PSS affect all players irrespective of their MSS. Future studies could examine whether these trends are also evident with relative speed thresholds.**

KEYWORDS: high-speed running, sprinting, soccer, mixed models, variability.

Received: 15 July 2024
Accepted: 22 February 2025

Corresponding author: kwn.patras@gmail.com

[1] *Democritus University of Thrace, Department of Physical Education and Sport Sciences, Komotini, Greece*
[2] *University Hospital of Ioannina, Department of Laboratory Medicine, Ioannina, Greece*

Introduction

Soccer is one of the most demanding team sport combining all physical abilities at a high level. The simultaneous demands on endurance, strength and speed during the official games create a multifaceted sports profile for the soccer players [3, 8]. With the aid of monitoring systems, practitioners are better able to identify those needs and modify the training process in order to culminate the potential for improved performance. Sustainable high performance in elite football is associated with well-developed speed skills, given that previous research has reported 16-27 sprint attempts (>25 km·h^{-1}) over the course of match at the highest level [9]. Additionally, others have reported that straight-line sprinting is the single most frequent action involved in goal-scoring [11]. Furthermore, recently reviewed data indicated that distances traveled during sprinting have been increasing in the top leagues [13]. The ability to reach high top speeds depends on various parameters including age, training and genetic characteristics [8, 23]. By closely monitoring and controlling the cumulative load associated with the different speed bands (>20 km·h^{-1} or >25 km·h^{-1}), practitioners are able to adjust the training loads [12] with the main goal of achieving high performance standards and reducing injury incident [13].

Match-to-match high-intensity running performance varies according to the playing position [7, 9], resulting in a need for individualized treatment and approach of the soccer players as per the training and rehabilitation strategies. However, the effect of individual player traits, such as maximal sprinting speed (MSS), on-match high intensity indices, i.e., very high speed running distance (VHSR), sprinting distance (SpD) and match peak sprinting speed (PSS), have not been directly tested [6, 15]. MSS differs between players and it has been shown that it may affect match PSS and/or SpD in youth soccer players [1, 20]; however, this has not been examined at the professional level. High-intensity match loads (VHSR, SpD) are associated with high levels of neuromuscular fatigue; thus, when comparing high-intensity training loads, adjustments must be made for any potential systematic effect of maximal sprinting before any decisions for interventions are made. In addition, quantifying the magnitude of the effect of MSS must be made in relation to the match-to-match variability of the response variables (i.e., VHSR or SpD) [25]. This approach will ensure that (any) systematic effect has practical significance and does not represent the noise associated with the inherent variable and stochastic nature of soccer [23, 24].

Aim of Study

There is no previous study that has examined the effect of having higher MSS on VHSR, SpD and match PSS. Therefore, the purpose of the present study was to estimate the effect of maximal sprinting traits on VHSR, SpD and match PSS in professional football players.

Materials and Methods

Participants

The data from 16 elite professional players (28.1 ± 5.5 years; height: 181.3 ± 7.4 cm; body mass: 76.9 ± 8.5 kg) competing in the 1st Cypriot League were analyzed. These players participated on average in 10 hours of soccer specific training and competitive play per week (an average of 5-6 sessions + 1-2 games per week) alongside almost daily core, lower and upper body workout in the gym depending upon team's schedule (approx. 20 min). The team played a 4-4-2 formation for the entire league with some minor adjustments depending on the scoreline and unexpected incidents that occurred during the matches. Players from different positions (27) were included in the analysis: forwards (FW), central midfielders (CM), wide midfielders (WM), fullbacks (FB), and central defenders (CD). Additionally, participants had to meet the following criteria: (i) players had to play the full duration of the match; (ii) goalkeepers were excluded from the analysis. Although no specific intervention was required for this study, the club and participants were informed of the risks, benefits and objectives of the study and gave their written consent before the initiation of the study.

Procedures

The analysis was carried out throughout the entire competitive season, from the first official game to the last one. External training loads and match running performances were recorded during all training sessions and official matches using GPS wearable devices at a sampling frequency of 10 Hz (OptimEye S5, Catapult Innovations, Australia). Moreover, this device has been certified according to the FIFA quality standard for time-motion analysis [24] after rigorous testing procedures [23, 25]. The devices were activated according to the manufacturer's instructions and GPS data were downloaded onto a portable PC and analyzed using dedicated software (Catapult Open Field Software) and an electronic spreadsheet (Excel, Microsoft Corporation, USA).

Top elite players with high soccer professional experience (9 ± 7 years) possess great acceleration capacities, which allow them to reach their MSS within even shorter distances; this suggests that training sessions and competitive games have been enough to determine MSS for the majority of them. Also, the peak speed reached during similar speed related soccer training sessions was shown to be similar to the MSS reached during proper speed testing [16]. All raw data were exported from the Catapult software (training and match) to be processed with an electronic spreadsheet (Excel, Microsoft Corporation, USA). The variables recorded in the present study were: (i) VHSR as the distance covered in the 20-25 km·h^{-1} band, (ii) SpD as the distance covered in the >25 km·h^{-1} band, (iii) PSS; the PSS recorded in every game. MSS (i.e., the highest sprinting speed throughout the season) was measured during either (1) top-speed training sessions (i.e., 6-8 repetitions of 30 to 40-m sprints and/or finishing soccer drills) or (2) large-sided games (LSG).

Statistical analysis

The dependent variables of the present study were the VHSR, SpD and PSS. The analyses were performed in the environment of the open-source programming language R using tidyverse for data wrangling and visualization and lme4 for hierarchical modeling [4, 25]. We estimated sources of variability (between-player, between-match, and the residual within-player variability) and provided reference values for interpreting the effects of MSS on the response variables [28]. The fixed effects for all response variables included a linear trend for the seasonal progression and a linear trend for the between-player MSS effect, accounting for the player-to-player deviation in MSS. The random effects in the model were SDs and included player ID to estimate between athletes' pure differences, game ID to account for the effect of match-related factors on the response variables and the model residual representing within athlete game-to-game variability [4, 14, 24, 25]. All models were estimated via Maximum Likelihood (REML), and model appropriateness was verified by examining the QQ-plots of the studentized residuals [4]. Each random effect representing a source of variability was expressed both in raw units by modeling the original data, and in percentage units (CV%) by first log-transforming the original data before modeling, and then back-transforming each estimate after the modeling was done [4, 14, 24, 25]. Within-athlete, between-athlete and between-game SDs (variability) were calculated as the square root of the model residual, the square root of the athlete ID variance, and the square root of the game ID variance, respectively [14, 28].

The effects were summarized by the mean (±90% confidence intervals). Inferences about the effects were made by interpreting the 90% CI in relation to the smallest worthwhile change (SWC). We specified SWC as 0.2 × observed between-player variability (the pooled between- and within-player SD) [28]. We used non-clinical magnitude-based decisions for inferential purposes; effects were deemed unclear if there was >5% chance for the true value of the effect to be substantially positive (or higher) and >5% chance to be substantially negative (lower). Otherwise, the effect was declared clear and we reported the observed magnitude and the chances as substantial and/or trivial [14].

Results

The observed VHSR, SpD, PSS and MSS were 377.8 ± 146.7m, 140.8 ± 93.8 m, 30.7 ± 2.0 km·h^{-1} and 33.5 ± 1.4 km·h^{-1}. Individual observed VHSR, SpD and PSS values per games as well as the associated model expected mean seasonal trends are presented in Figure 1; magnitudes of the effects as well as qualitative descriptors are provided in Table 1.

There was a very likely substantial seasonal reduction in model expected PSS (–1.2 km·h^{-1} [90% CI: –1.9 to –0.4], –3.7% [90% CI: –5.9 to –1.4]). The seasonal trends for model expected VHSR (21.5 m [90% CI: –35.1 to 78.2], 4.5% [90% CI: –10.1 to 21.5]) and model expected SpD (–28.0 m [90% CI: –64.9 to 9.2], –16.7% [90% CI: –39.9 to 16.2]) were not as clear (Figure 2). Higher MSS was associated with very likely substantially higher model expected SpD (48.2 m [90% CI: 26.0 to 70.2], 41.0% [90% CI: 15.1 to 72.1]) and very likely substantially higher model expected PSS (1.1 km·h^{-1} [90% CI: 0.8 to 1.4], 3.6% [90% CI: 2.5 to 4.6]) (Figure 2). Model expected mean VHSR, SpD and PSS were 394.1 m [90% CI: 329.6-458.5], 153.0 m [90% CI: 129.4-181.6]

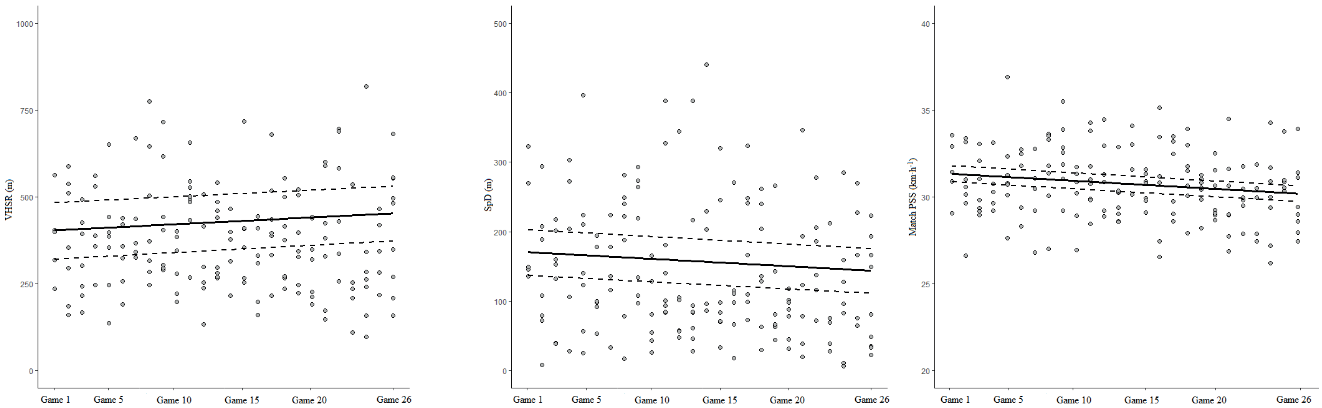


Figure 1. Seasonal trends in match physical performance for very high speed running distance (VHSR), sprinting distance (SpD), peak sprinting speed (PSS). Data are presented as individual player match observations (points) and population mean expected trend (black solid line) with 90% confidence intervals (dotted lines)

Table 1. Effect magnitudes for MSS and seasonal trend for all three response variables

Model	Effect	Magnitude	Chances	Qualitative descriptor
VHSR (m)	MSS	47.8 (–16.4; 79.1)	68.7/28.5/2.7	possibly substantial ↑ and possibly trivial
	seasonal trend	21.5 (–35.1; 78.2)	41.4/51.3/7.3	unclear
SpD (m)	MSS	48.2 (26.0; 70.2)	99.0/2.0/0.0	very likely substantial ↑
	seasonal trend	–28.0 (–64.9; 9.2)	3.3/23.1/73.6	possibly substantial ↓
PSS ($km \cdot h^{-1}$)	MSS	1.1 (0.8; 1.4)	99.9/0.1/0.0	very likely substantial ↑
	seasonal trend	–1.2 (–1.9; –0.4)	0.1/2.4/97.6	very likely substantial ↓
VHSR (%)	MSS	4.5 (–10.1; 21.5)	35.7/55.1/9.2	unclear
	seasonal trend	7.1 (–11.0; 29.2)	46.9/43.2/9.9	unclear
SpD (%)	MSS	41.0 (15.1; 72.1)	95.5/4.5/0.0	very likely substantial ↑
	seasonal trend	–16.7 (–39.9; 16.2)	5.9/33.5/60.7	unclear
PSS (%)	MSS	3.6 (2.5; 4.6)	99.9/0.1/0.0	very likely substantial ↑
	seasonal trend	–3.7 (–5.9; –1.4)	0.1/2.6/97.3	very likely substantial ↓

Note: MSS – maximal sprinting speed, VHSR – very high-speed running distance, SpD – sprinting distance, PSS – peak sprinting speed
Estimates are presented as mean ± 90% CI.

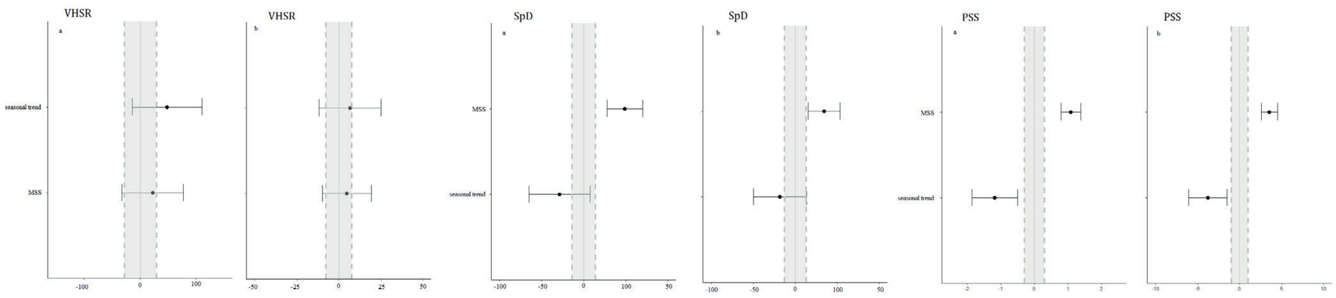
Table 2. Variability of match VHSR and PSS expressed in raw units and as coefficient of variation (%)

Response metric		Variability		
		Within-player	Between-player	Between-games
SD (90% CI)[a]	VHSR (m)	71.1 (64.4; 79.1)	125.1 (94.5; 174.5)	48.8 (35.3; 66.8)
	SpD (m)	52.4 (47.4; 58.2)	46.2 (33.4; 66.2)	24.0 (14.2; 35.3)
	PSS ($km \cdot h^{-1}$)	1.4 (1.3; 1.6)	0.5 (0.2; 0.8)	0.3 (0.0; 0.6)
	PSS_{rel} (%)	4.2 (3.8; 4.7)	1.5 (0.8; 2.5)	0.8 (0.0; 1.6)
CV (90% CI)[b]	VHSR (m)	21.6 (19.4; 24.2)	39.1 (28.3; 58.5)	15.4 (11.1; 21.5)
	SpD (m)	64.7 (57.1; 74.1)	52.0 (35.0; 82.6)	22.0 (10.6; 35.4)
	PSS ($km \cdot h^{-1}$)	4.8 (4.3; 5.3)	1.7 (0.8; 2.8)	0.8 (0.0; 1.8)
	PSS_{rel} (%)	4.8 (4.3; 5.3)	1.7 (0.8; 2.8)	0.8 (0.0; 1.8)

Note: SD – standard deviation, CI – confidence intervals, CV – coefficient of variation, VHSR – very high speed running distance, SpD – sprinting distance, PSS – peak sprinting speed, PSS_{rel} – relative peak sprinting speed
Estimates are presented as mean (90% CI).
[a] Values are presented in the original metric unit of measurement. [b] Values are presented as a percentage of the mean.

and 30.9 $km \cdot h^{-1}$ [90% CI: 30.5-31.4] after adjusting for seasonal trend and differences in MSS.

The estimates of within-player, between-player and between-game variabilities in each response variable, expressed in raw (SD) and % (CV) units are presented in Table 2. All sources of variability were substantially lower for PSS compared to the other response variables. When expressed as SDs (m), sources of variability were greater for VHSR compared to SpD and PSS, but when expressed as CVs (%), SpD had higher variability. The observed between-player variability (combined pure between-player and within-player) for VHSR, SpD and PSS was 143.9 m (38.5%), 69.8 m (65.1%) and 1.5 $km \cdot h^{-1}$ (5%).



MSS – maximal sprinting speed

Figure 2. Magnitude of effects (mean ± 90% CI) in relation to the smallest worthwhile change (gray-shaded area between the dotted lines) for very high speed running distance (VHSR), sprinting distance (SpD) and match peak sprinting speed (PSS). All effects are given in raw absolute units (a) and as percent (b)

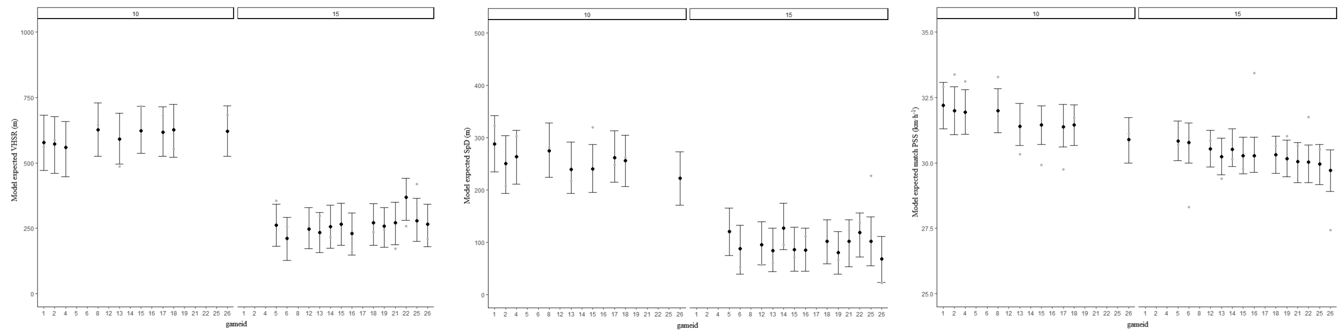


Figure 3. Model expected values for very high speed running distance (VHSR), sprinting distance (SpD) and match peak sprinting speed (PSS) for a player with average (player 15) and a player with high (player 10) maximal sprinting speed. Model expected values are presented as black points with 90% confidence intervals; gray points indicate actual (observed) performance

Figure 3 displays observed and model expected match VHSR, SpD and PSS for two players with typical and typically high MSS (33.4 km·h^{-1} vs 35.0 km·h^{-1}). The effect of interest is based off on the individual random effects (between-player variability and between-match variability).

Discussion

The purpose of the present study was to estimate the effect of MSS on match VHSR, SpD and PSS after adjusting for season trends. Although sprint running capabilities are advantageous for elite soccer performance [9, 11], to the best of our knowledge no study has explored the relevance of MSS traits on match physical performance in professional players. The main findings of this case study were: (a) faster players cover on average very likely substantially more SpD, (b) faster players reach on average very likely substantial higher absolute PSS during games than their slower counterparts, (c) absolute PSS shows on average a very likely substantial seasonal decrease that affects all players irrespective of their MSS.

The tactical constraints associated with soccer match play are likely to impact upon the relationship between MSS (i.e., the intrinsic ability to cover a set distance in the minimum possible time as determined via a field test) and actual sprinting output during matches [9, 11]. Despite this possible modulation, faster players, as assessed via field testing, are very likely to reach substantially greater absolute speeds during match play on average, suggesting a direct impact of MSS on on-field physical performance [9]. To the best of our knowledge only two studies on youth soccer players have examined the influence of MSS on PSS [1, 20]. Both of these studies concluded that higher MSS has a clear beneficial effect on match PSS. For example, given that higher PSS was reached by the fastest players and that all players used a high percentage of their MSS, Mendez-Villanueva et al. [20] concluded that MSS can actually impact what a player can do under match conditions. The present study extended this finding to high level professional players and further quantified the difference in PSS to be ~3.5% on average between faster and slower players in terms of MSS.

Our results further indicated that faster players cover on average 41% more SpD compared to slower players; this difference would translate into ~153 m vs ~201 m on average for a player with typical MSS vs a player with typically high MSS after adjusting for seasonal trends. To put those numbers in perspective, typical SpD range from 156 m and 184 m for elite Croatian players and in the French Ligue 1 respectively to ~300 m in the English Premier League [13]. Sprinting has a high energy cost and is associated with high levels of neuromuscular fatigue. Thus, simply monitoring cumulative distance >25.2 km·h^{-1} without knowledge of the individual MSS traits may lead to wrong conclusions; the systematically higher SpD of faster players needs to be accounted for when comparing players [25]. Identifying, for example, two players with the same volume of external load at these intensities but with different MSS, leads to a more or less metabolic cost during these actions that may affect overall performance and may expose to injuries at a higher rate [5, 18].

In addition to the substantial effect of MSS on SpD and PSS, we also demonstrated a substantial negative seasonal effect on PSS, namely that the players, irrespective of their MSS, reached lower match PSS as the season progressed. To the best of our knowledge only one study has examined the effect of seasonal trend on match PSS [25]. In contrast to our findings, these authors reported an inconclusive seasonal trend (0.2 km·h^{-1} [–0.5 to 1.0], 0.8% [–1.5 to 3.2]) for a professional soccer team from the Spanish LaLiga [25]. Although absolute PSS levels did not differ drastically (30.9 km·h^{-1} vs 31.6 km·h^{-1}), the Spanish team did not show evidence of downwards trends. In this regard, there is a number of potential mediators that may influence these different trends (differences in ball possession, maintained fitness levels, tactical style adjustments) [25]. In addition, our estimate of the PSS seasonal tend had better precision despite the latter study having a ~50% higher games sample (26 vs 42). Therefore, seasonal trends need to be analyzed from a context-specific perspective in order to fully appreciate the magnitude and direction of the observed changes. Moreover, given the fact that the players were affected irrespective of their MSS, we may seek for mediators with a global effect rather than player-specific. Therefore, we hypothesize that the substantial negative seasonal PSS trend may be indicative of fatigue accumulation as the season progressed. On the other hand, the adoption of a slower game tempo through more ball possession or more concrete defensive formats or even some combination of tactical and physiological factors, may offer further potential explanations.

There was a possibly substantial and possibly trivial effect of MSS on VHSR; this indicates that it is very unlikely for faster players to cover on average substantially less VHSR compared to slower players. Our estimate of VHSR ~394 m (90% CI: 330-460) (after adjusting for seasonal trend and MSS) is quite lower from what has been previously reviewed for the English Premier League (~700 m), the French Ligue 1 (~600 m) and only marginally comparable to elite Croatian players (~460 m) [13]. In addition, whilst our results indicated an unclear seasonal trend for VHSR, a 25% rice (90% CI: 3-52%) has been previously reported for Spanish professional soccer players [25]. Collectively the differences between the present study and Oliva-Lozano et al. [25] probably indicate that practitioners need to assess seasonal trends on an as-needed basis since both the direction and magnitude of the changes may reveal unexpected patterns.

Regarding the estimates of between-player, between-match and within-player variabilities, we observed higher magnitudes for SpD compared to the other response variables. These results are consistent across studies reporting increased variability with running intensity [4, 8, 23]. However, despite the fact that SpD had high variability, the effect of MSS was substantial which probably indicates the robustness and practical value of our finding. Additionally, our approach to partition sources of variability revealed that between-game was lower, in both absolute and relative terms, compared to either between- or within-player variability (Table 2). This suggested that match-related factors are associated with lower variability compared to mean differences between players (between-player variability) or to match-to-match differences within a given player (within-player variability). Moreover, whilst between-player variability was somewhat higher for VHSR, the opposite was true for both SpD and PSS.

There are some general limitations associated with the present study that need to be addressed in order to guide future similar research designs. The present study included only one professional soccer team, thus, the sample size included the most regular players (n = 16). In addition, the present study utilized a GPS – based monitoring system; therefore, similar studies utilizing other monitoring tools, such as local positioning systems, are needed before adopting the presented results. It should also be acknowledged that all analyses reported in the present work were conducted in terms of absolute loads (distances accumulated within fixed predefined speed bands) without taking into consideration players' individual speed profiles [18, 22]. To our knowledge, there has been no study for elite soccer players [1, 20, 26] that analyzed the effect of MSS on VHSR and SpD using the relative speed thresholds. This process may help the coaches to better understand the effort put in by the football players during the games and to adapt the training process accordingly with the aim of better achieving the demands of the game and reducing injuries [2, 10, 17, 21].

Conclusions

In conclusion, faster players cover on average very likely substantially more SpD and reach higher absolute PSS during games compared to slower players. A very likely substantial seasonal decrease in PSS affects all players, irrespective of their MSS. When comparing high-intensity training loads adjustments, sport scientists should account for the systematic effect of MSS differences between players before any decisions for interventions are made. In addition, interventions that may blunt the seasonal decrease in match peak speed could also be relevant. Future studies could examine whether relative speed thresholds or position-specific effects may modify these trends.

Conflict of Interest

The authors have no conflicts of interest to report.

References

1. Al Haddad H, Simpson BM, Buchheit M, Di Salvo V, Mendez-Villanueva A. Peak match speed and maximal sprinting speed in young soccer players: effect of age and playing position. Int J Sports Physiol Perform. 2015;10(7):888-896.
2. Baena-Raya A, Soriano-Maldonado A, Conceicao F, Jimenez-Reyes P, Rodríguez-Perez MA. Association of the vertical and horizontal force-velocity profile and acceleration with change of direction ability in various sports. Eur J Sport Sci. 2021;21(12):1659-1667. https://doi.org/10.1080/17461391.2020.1856934
3. Bangsbo J, Mohr M, Krustrup P. Physical and metabolic demands of training and match-play in the elite football player. J Sports Sci. 2006;24(7):665-674. https://doi.org/10.1080/02640410500482529
4. Baptista I, Winther AK, Johansen D, Randers MB, Pedersen S, Pettersen SA. The variability of physical match demands in elite women's football. Sci Med Footb. 2022;6(5):559-565. https://doi.org/10.1080/24733938.2022.2027999
5. Colby MJ, Dawson B, Peeling P, Heasman J, Rogalski B, Drew MK, et al. Improvement of prediction of noncontact injury in elite Australian footballers with repeated exposure to established high-risk workload scenarios. Int J Sports Physiol Perform. 2018;13(9):1130-1135. https://doi.org/10.1123/ijspp.2017-0696
6. De Hoyo M, Sanudo B, Suarez-Arrones L, Carrasco L, Joel T, Domínguez-Cobo S, et al. Analysis of the acceleration profile according to initial speed and positional role in elite professional male soccer players. J Sports Med Phys Fit. 2018;58(12):1774-1780. https://doi.org/10.23736/S0022-4707.17.08003-3
7. Dellal A, Wong DP, Moalla W, Chamari K. Physical and technical activity of soccer players in the French first league-with special reference to their playing position. Int SportMed J. 2010;11(2):278-290.
8. Di Salvo V, Gregson W, Atkinson G, Tordoff P, Drust B. Analysis of high intensity activity in Premier League soccer. Int J Sports Med. 2009;30(3):205-212. https://doi.org/10.1055/s-0028-1105950
9. Di Salvo V, Baron R, Gonzalez-Haro C, Gormasz C, Pigozzi F, Bachl N. Sprinting analysis of elite soccer players during European Champions League and UEFA Cup matches. J Sports Sci. 2010;28(14):1489-1494. https://doi.org/10.1080/02640414.2010.521166
10. Edouard P, Mendiguchia J, Guex K, Lahti J, Samozino P, Morin JB. Sprinting: a potential vaccine for hamstring injury? Sport Perform Sci Rep. 2019;48:v1.
11. Faude O, Koch T, Meyer T. Straight sprinting is the most frequent action in goal situations in professional football. J Sports Sci. 2012;30(7):625-631. https://doi.org/10.1080/02640414.2012.665940
12. Ferro A, Villacieros J, Floria P, Graupera JL. Analysis of speed performance in soccer by playing position and a sports level using a laser system. J Hum Kin. 2014;44:143-153. https://doi.org/10.2478/hukin-2014-0120
13. Gualtieri A, Rampinini E, Dello Iacono A, Beato M. High-speed running and sprinting in professional adult soccer: current thresholds definition, match demands and training strategies. A systematic review. Front Sports Act Living. 2023;5:1116293. https://doi.org/10.3389/fspor.2023.1116293
14. Hopkins WG, Marshall SW, Batterham AM, Hanin J. Progressive statistics for studies in sports medicine and exercise science. Med Sci Sports Exerc. 2009;41(1):3-13. https://doi.org/10.1249/MSS.0b013e31818cb278
15. Jimenez-Reyes P, Garcia-Ramos A, Parraga--Montilla JA, Morcillo-Losa JA, Cuadrado-Penafiel V, Castano-Zambudio A, et al. Seasonal changes in the sprint acceleration force-velocity profile of elite male soccer players. J Strength Cond Res. 2020;36(1):70-74. https://doi.org/10.1519/JSC.0000000000003513
16. Kyprianou E, Di Salvo V, Lolli L, Al Haddad H, Mendez Villanueva A, Gregson W, Weston M. To measure peak

velocity in soccer, let the players sprint. J Strength Cond Res. 2019;36(1):273-276. https://doi.org/10.1519/JSC.0000000000003406
17. Malone JJ, Lovell R, Varley MC, Coutts AJ. Unpacking the black box: applications and considerations for using GPS devices in sport. Int J Sports Physiol Perform. 2017;12(S2):S18-S26. https://doi.org/10.1123/ijspp.2016-0236
18. Malone S, Roe M, Doran DA, Gabbett TJ, Collins K. High chronic training loads and exposure to bouts of maximal velocity running reduce injury risk in elite gaelic football. J Sci Med Sport. 2017;20(3):250-254. https://doi.org/10.1016/j.jsams.2016.08.005
19. Mendez-Villanueva A, Buchheit M, Simpson B, Peltola E, Bourdon P. Does on-field sprinting performance in young soccer players depend on how fast they *can* run or how fast they *do* run? J Strength Cond Res. 2011;25(9):2634-2638. https://doi.org/10.1519/JSC.0b013e318201c281
20. Mendez-Villanueva A, Buchheit M, Simpson BM, Bourdon PC. Match play intensity distribution in youth soccer. Int J Sport Med. 2013;34(2):101-110. https://doi.org/10.1055/s-0032-1306323
21. Morin JB, Gimenez P, Edouard P, Arnal P, Reyes PJ, Samozino P, et al. Sprint acceleration mechanics: the major role of hamstrings in horizontal force production. Front Physiol. 2015;6:404. https://doi.org/10.3389/fphys.2015.00404
22. O'Connor F, Thornton HR, Ritchie D, Anderson J, Bull L, Rigby A, et al. Greater association of relative thresholds than absolute thresholds with noncontact lower-body injury in professional Australian rules footballers: implications for sprint monitoring. Int J Sports Physiol Perform. 2020;15(2):204-212. https://doi.org/10.1123/ijspp.2019-0015
23. Oliva-Lozano JM, Fortes V, Krustrup P, Muyor JM. Acceleration and sprint profiles of professional male football players in relation to playing position. PLoS One. 2020;15(8):e0236959. https://doi.org/10.1371/journal.pone.0236959
24. Oliva-Lozano JM, Muyor JM. Understanding the FIFA quality performance reports for electronic performance and tracking systems: from science to practice. Sci Med Footb. 2022;6(3):398-403. https://doi.org/10.1080/24733938.2021.1984557
25. Oliva-Lozano JM, Muyor JM, Fortes V, McLaren SJ. Decomposing the variability of match physical performance in professional soccer: implications for monitoring individuals. Eur J Sport Sci. 2021;21(11):1588-1596. https://doi.org/10.1080/17461391.2020.1842513
26. Rico-Gonzalez M, Arcos AL, Nakamura FY, Moura FA, Pino-Ortega J. The use of technology and sampling frequency to measure variables of tactical positioning in team sports: a systematic review. Res Sports Med. 2020;28(2):279-292. https://doi.org/10.1080/15438627.2019.1660879
27. Robertson S, Duthie GM, Ball K, Spencer B, Serpiello FR, Haycraft J, et al. Challenges and considerations in determining the quality of electronic performance & tracking systems for team sports. Front Sports Act Living. 2023;5:1266522. https://doi.org/10.3389/fspor.2023.1266522
28. Wiig H, Andersen TE, Luteberget LS, Spencer M. Individual response to external training load in elite football players. Int J Sports Physiol Perform. 2020;15(5):696-704. https://doi.org/10.1123/ijspp.2019-0453