Original Article

American Journal of Men's Health
September-October 1–15
© The Author(s) 2021
Article reuse guidelines:
sagepub.com/journals-permissions
DOI: 10.1177/15579883211054353
journals.sagepub.com/home/jmh
SAGE

Higher Playing Times Accumulated Across Entire Games and Prior to Intense Passages Reduce the Peak Demands Reached by Elite, Junior, Male Basketball Players

Enrique Alonso Pérez-Chao[1,2], Alberto Lorenzo[1], Aaron Scanlan[3], Pedro Lisboa[4], Carlos Sosa[1], and Miguel Ángel Gómez[1]

Abstract

The aim of this study was to analyze the effects of different factors on the external peak demands (PD) encountered by elite, junior, male basketball players in games, including the (1) total playing time during games and (2) playing time accumulated directly prior to each PD episode. Workload variables included the PD for total distance, distance covered in different intensity zones, accelerations >2 m·s^{-2} (ACC), decelerations <-2 m·s^{-2} (DEC), and PlayerLoad. PD were calculated across different sample durations for each variable. Linear mixed models were used to identify differences in PD between groups based on playing times. PD for total distance (5-min window), high-speed running (>18 km·h^{-1}) distance (2-min window), and ACC (30-s, 45-s, 1-min, 2-min, and 5-min windows) were significantly ($p < .05$) higher for players who completed lower total playing times (16.6 ± 2.4 min) than players who completed higher total playing times (25.0 ± 3.4 min). The PD for total distance (30-s, 45-s, 1-min, and 2-min windows), high-speed running distance (30-s and 5-min windows), and PlayerLoad (1-min and 2-min windows) were significantly ($p <$ .05) higher for players who accumulated lower playing times before each PD episode than players who accumulated higher playing times before each PD episode. Players who undertake less playing time overall and prior to each PD episode can reach higher peak external loads aggregated across varied time windows. These findings can inform tactical coaching decisions during games for high external loads to be accomplished during important passages of play.

Keywords

technology, load management, worst case scenario, team sports, load monitoring

Received August 6, 2021; revised September 28, 2021; accepted October 1, 2021

Technological innovations including microsensors containing accelerometers, gyroscopes, and magnetometers (Chambers et al., 2015; Gabbett, 2013) as well as local positioning systems (LPS) (Hodder et al., 2020; Serpiello et al., 2018) permit external player demands to be precisely quantified during training and games in basketball. Data derived from these technologies demonstrate basketball is a complex, intermittent, high-intensity sport in which the ability to execute technical skills while concurrently performing repeated accelerations, decelerations, changes in direction, and jumps is crucial for success (Montgomery et al., 2010; O'grady et al., 2020; Stojanović et al., 2018). Using these data, basketball coaches often

[1]Facultad de ciencias de la actividad física y del deporte, Universidad Politécnica de Madrid, Madrid, Comunidad de Madrid, España
[2]Faculty of Sports Sciences, University Alfonso X el Sabio, Villanueva de la Cañada, Community of Madrid, Spain
[3]Human Exercise and Training Laboratory, School of Health, Medical and Applied Sciences, Central Queensland University, Rockhampton, Queensland, Australia
[4]Faculty of Sports, University of Porto, Porto, Portugal

Corresponding Author:
Alberto Lorenzo, Facultad de ciencias de la actividad física y del deporte, Universidad Politécnica de Madrid, Martín Fierro,7, Madrid, Comunidad de Madrid 28040, España.
Email: alberto.lorenzo@upm.es

attempt to expose players to training demands that adequately prepare them for the demands likely to be faced during gameplay (Alonso et al., 2020). In this regard, quantifying the most demanding passages experienced during games is essential to tailor precise training plans that equip players with fitness capacities to best endure game demands while successfully executing key technical skills (Alonso et al., 2020).

Many investigations quantifying the game demands experienced by basketball players have measured the average intensity across entire games; however, this approach does not capture the most demanding passages of games (Abdelkrim et al., 2007; Puente et al., 2016). In turn, the peak demand (PD), defined as the most intense activity experienced by players for a selected variable across a specified timeframe of interest (Alonso et al., 2020), has been quantified in basketball players using many external variables (e.g., PlayerLoad, distance, accelerations, and decelerations) and time windows (e.g. 30 s, 45 s, 1 min, 5 min, and 10 min) (Alonso et al., 2020; Fox, Conte, et al., 2020; Fox, Salazar, et al., 2020; Vázquez-Guerrero et al., 2020; Vázquez-Guerrero & Garcia, 2020). In this regard, the impact of different factors on the PD attained by players during basketball games has been explored, including the effects of player position (Alonso et al., 2020; Fox, Conte, et al., 2020), game score-line (Vázquez-Guerrero et al., 2020), and game schedule (Pino-Ortega et al., 2019). While these previous studies offer useful insight, the effects of playing time on the PD experienced by basketball players during games have not been examined. In this way, the individualized playing time of players is a key tactical element in basketball that can be manipulated by coaches to optimize team performance through various means such as mitigating player fatigue during key stages of games (Edwards et al., 2018).

Fatigue is defined as a suboptimal psychophysiological state encompassing mental and physical mechanisms, concomitant with physical exertion (Phillips, 2015). Data from previous research indirectly suggest starting, male, semi-professional basketball players with greater playing times (33.2 $\pm$ 1.2 min) attain higher external PD (PlayerLoad) during games than bench players with lower playing times (8.7 $\pm$ 6.0 min) across time windows ranging from 30 s to 5 min (Fox, Conte, et al., 2020). However, the categorization of players into starter and bench groups in this previous research (Fox, Conte, et al., 2020) may have contributed to these findings with bench players being repeatedly substituted out of games, limiting their opportunity to undertake intense external loads and reach high PD across varied time windows. Consequently, further research is needed to ascertain the specific effects of playing time across entire games as well as prior to PD episodes, which will provide useful evidence for coaches to formulate precise player management strategies (e.g., substitutions, use of time-outs) to optimize their peak external outputs during key passages of play.

Therefore, the aim of this study was to analyze the effects of playing time on the external PD experienced during basketball games. Specifically, the effects of (1) total playing time during games and (2) playing time accumulated directly prior to each external PD episode were examined. It was hypothesized that the highest external PD would be obtained by players who participated less overall and directly before each PD episode during games.

Materials and Methods

Sample

Elite, junior, male basketball players (n = 13, mean $\pm$ standard deviation: age: 16.6 $\pm$ 1.0 years, height: 198 $\pm$ 8 cm, body mass: 87.8 $\pm$ 7.7 kg) were monitored during nine official home games in the same stadium during the 2019–2020 season. Players were competing in the under 18 years of age (U18) Madrid regional basketball league. Game samples from each player were only retained in the final analysis if they completed a minimum of 15-min playing time derived from devices in that particular game. Game samples where players had less than 15 min of playing time derived from devices were excluded from the final analyses. Furthermore, players had to complete 15 min of playing time in at least five games for inclusion in the study. In this regard, three players originally recruited (i.e., n = 16) were excluded from the final analysis, resulting in 13 players being retained in the study. Overall, 73 game samples across the 13 players were included in analyses. Participants and their parents or legal guardians were informed of the aims, risks, and benefits of the study before giving written consent to allow the collection of data for scientific purposes. The study procedures were approved by an institutional human ethics committee and were designed according to the Declaration of Helsinki (Harriss & Atkinson, 2014) with the Fortaleza actualization (Hellmann et al., 2014).

Procedures

During games, each player wore a monitoring device (ClearSky S7, Catapult Sports, Melbourne, Australia) inserted into a fitted neoprene vest under regular playing attire and positioned on the upper thoracic spine between the scapulae (Hodder et al., 2020). Each device contained microsensor technology consisting of an accelerometer ($\pm$16 g, 100 Hz), magnetometer ($\pm$4.900 µT, 100 Hz), and gyroscope (up to 2000 deg/s, 100 Hz). Each device

Table 1. Movement Intensity Zones Detected With the Local Positioning System Technology.

Zones	Speed
Standing-walking	<7 km·h^{-1}
Jogging	7.01–14 km·h^{-1}
Running	14.01–18 km·h^{-1}
High-speed running	>18 km·h^{-1}

was also interfaced with an LPS sampling at 10 Hz. The LPS was an ultra-wide band, 4 GHz transmitting system equipped with 24 anchors positioned around the perimeter of stadium. The LPS technology (ClearSky by Catapult) used in this study has been supported as valid in measuring distance, speed, and accelerations (Hodder et al., 2020; Luteberget et al., 2018; Serpiello et al., 2018), while similar LPS technology has been shown to be reliable (coefficient of variation (CV) <5%) in measuring distance and speed variables (Gómez Carmona et al., 2019; Hoppe et al., 2018). All players were familiar with the monitoring technology as they had worn the devices during training sessions and games in the previous season. Devices were turned on ~20–40 min before the warm-up phase prior to each game, and players wore the same device throughout the study period to avoid inter-unit variation in outputs (Castellano et al., 2011; Johnston et al., 2014; Nicolella et al., 2018).

Variables

All microsensor and LPS raw data were extracted at 1-s intervals for each player and inputted into customized Microsoft Excel (version 16.0, Microsoft Corporation, Redmond, WA) spreadsheets for further analysis. PDs were then determined for each variable in absolute values across different time windows as rolling averages, which is a more precise technique to measure PDs than fixed methods (Cunningham et al., 2018; Oliva-lozano et al., 2020) and has been previously used in basketball research (Alonso et al., 2020; Vázquez-Guerrero et al., 2020). Computation of rolling averages commenced at the beginning of each quarter and ceased at the end of the same quarter. PDs were calculated for each variable in each quarter in each game for each player across 30-s, 45-s, 1-min, 2-min, and 5-min windows. These time windows were chosen given they have been identified as the most practical to consider in basketball (Alonso et al., 2020; Fox, Salazar, et al., 2020; Vázquez-Guerrero et al., 2020).

PDs were calculated for several external load variables including total distance (m) covered, distance (m) covered in different velocity-mediated intensity zones based on zone cutpoints defined in previous basketball research (Sosa et al., 2021) (Table 1), accelerations (count) >2 m·s^{-2} (dwell time: 0.3 s), decelerations (count) <-2 m·s^{-2} (dwell time: 0.3 s), and PlayerLoad (PL, arbitrary units [AU]). PL was calculated as the square root of the sum of the instantaneous rate of change in acceleration in the three movement planes (x-, y, and z-axis) using the following formula (Brown & Greig, 2015),

$$PlayerLoad^{\text{TM}} = \left[\begin{array}{l} \sqrt{\left(fwd_{t=i+1} - fwd_{t=i}\right)^2} \\ +\sqrt{\left(side_{t=i+1} - side_{t=i}\right)^2} \\ +\sqrt{\left(up_{t=i+1} - up_{t=i}\right)^2} \end{array} \right] / 100,$$

where fwd indicates movement in the anterior-posterior direction, side indicates movement in the medial-lateral direction, up indicates vertical movement, and t represents time.

To identify the effect of playing time on each external PD variable, players were categorized into groups according to total playing time across games using the box score time and playing time accumulated directly prior to each PD derived from the devices. In this way, box score time was based on the playing time (min) derived from the official box score for games, which excludes any passages where the game clock is stopped (e.g., inter-quarter breaks, time-outs, fouls, out-of-bounds). Using a two-step cluster analysis for box score time, the sample was split into two groups (average silhouette = 0.7) as shown in Table 2.

The playing time accumulated directly prior to each external PD for each player, variable, and quarter was determined by playing time derived from devices. Playing time derived from devices included all stoppages in play such as free-throws, fouls, and out-of-bounds, but excluded break periods between quarters, time-outs, or time when players were substituted out of the game. Using two-step cluster analyses for the playing time accumulated before each PD, the sample was split into groups for each time window based on the time accumulated prior to each PD as shown in Table 3.

Statistical Analysis

The CV (%) was calculated for each external PD variable. The Shapiro-Wilk test confirmed the normality of all external PD variables. Separate linear mixed models were used to identify differences in each external PD variable for each time window between groups. In this way, group (according to total playing time (2 groups) and playing time prior to each external PD episode (2–4 groups depending on time window)) was included as a

Table 2. Cluster Analysis Identifying Groups Based on total playing time during games.

Measure	High Playing Time	Low Playing Time
Total game playing time (min)	25.0 ± 3.4	16.6 ± 2.4
Sample size (*N*)	142	128
Proportion of samples (%)	52.6%	47.4%
Bayesian information criterion	197.8	99.5

Note. Total game playing time presented as mean ± standard deviation for each group; sample size indicates the number of individual game samples included across all players.

Table 3. Cluster Analyses Identifying Groups Based on Playing Time (min) Accumulated Prior to Each External Peak Demands Episode During Games.

Time Window	Groups				Bayesian Information Criterion	Average Silhouette
30 s	***Low*** 16.8 ± 0.9 min (*N* = 139; 51.5%)		***High*** 55.5 ± 1.1 min (*N* = 131; 48.5%)		677.3	0.7
45 s	***Low*** 10.9 ± 0.9 min (*N* = 93; 34.4%)	***Medium*** 37.8 ± 1.0 min (*N* = 103; 38.1%)		***High*** 63.7 ± 1.6 min (*N* = 74; 27.4%)	598.8	0.6
1 min	***Low*** 17.1 ± 0.8 min (*N* = 139; 51.5%)		***High*** 55.5 ± 1.5 min (*N* = 131; 48.5%)		705.5	0.7
2 min	***Low*** 8.6 ± 1.0 min (*N* = 72; 26.7%)	***Low-medium*** 27.1 ± 0.7 min (*N* = 67; 24.8%)	***Medium-high*** 47.2 ± 1.3 min (*N* = 75; 27.8%)	***High*** 67.9 ± 1.4 min (*N* = 56; 20.7%)	546.6	0.6
5 min	***Low*** 19.4 ± 0.8 min (*N* = 140; 51.9%)		***High*** 57.5 ± 1.4 min (*N* = 130; 48.1%)		702.8	0.7

Note. Playing time prior to each external peak demands episode presented as mean ± standard deviation for each group; *N* = sample size encompassing the number of individual game samples included across all players, percentage value indicates the proportion of samples included in the group. Low = low prior playing time group; High = high prior playing time groups; Medium = medium prior playing time group; low-medium = low to medium prior playing time group; Medium-high = medium to high prior playing time group.

fixed factor, and player was included as a random factor in the linear mixed models. Bonferroni post hoc analyses were conducted where more than two groups were derived for the fixed factor in any cluster analysis. Statistical significance was set at an alpha level of $<.05$. To determine the practical meaningfulness of any differences, mean differences and Cohen's effect sizes (ES) with 95% confidence intervals were determined for all pairwise comparisons. ES were interpreted as: trivial: ≤ 0.20; small: 0.21–0.60; moderate: 0.61–1.20; large: 1.21–2.00; very large: 2.01–4.00; and extremely large: >4.00 (Hopkins et al., 2009). All analyses were conducted using IBM SPSS for Windows (version 23, IBM Corporation, Armonk, New York) and Microsoft Excel (version 16.0, Microsoft Corporation, Redmond, WA).

Results

Comparisons between groups for each external PD variable along with the CV% according to total playing time during games are shown in Figure 1 and Table 4. The lower total playing time group achieved significantly greater PD ($p < .05$, small) for total distance (5-min window), high-speed running (HSR) distance (2-min window), and accelerations (30-s, 45-s, 1-min, 2-min, and 5-min windows) than the higher total playing time group (Table 4).

Comparisons between groups for each external PD variable along with the CV% according to playing time accumulated prior to each PD episode are shown in Figure 2. Across 30-s windows, the low prior playing time group achieved significantly greater PD for total distance (F = 6.96, $p = .009$, small) and HSR distance (F = 4.64, $p = .03$, small) than the high prior playing time group. Across 45-s time windows, there was a significant group effect in PD for total distance (F = 4.01, $p = .02$) with post hoc analyses revealing the low prior playing time group attained higher PD for total distance ($p = .02$, small) than the high prior playing time group. Across 1-min time windows, the low prior playing time group

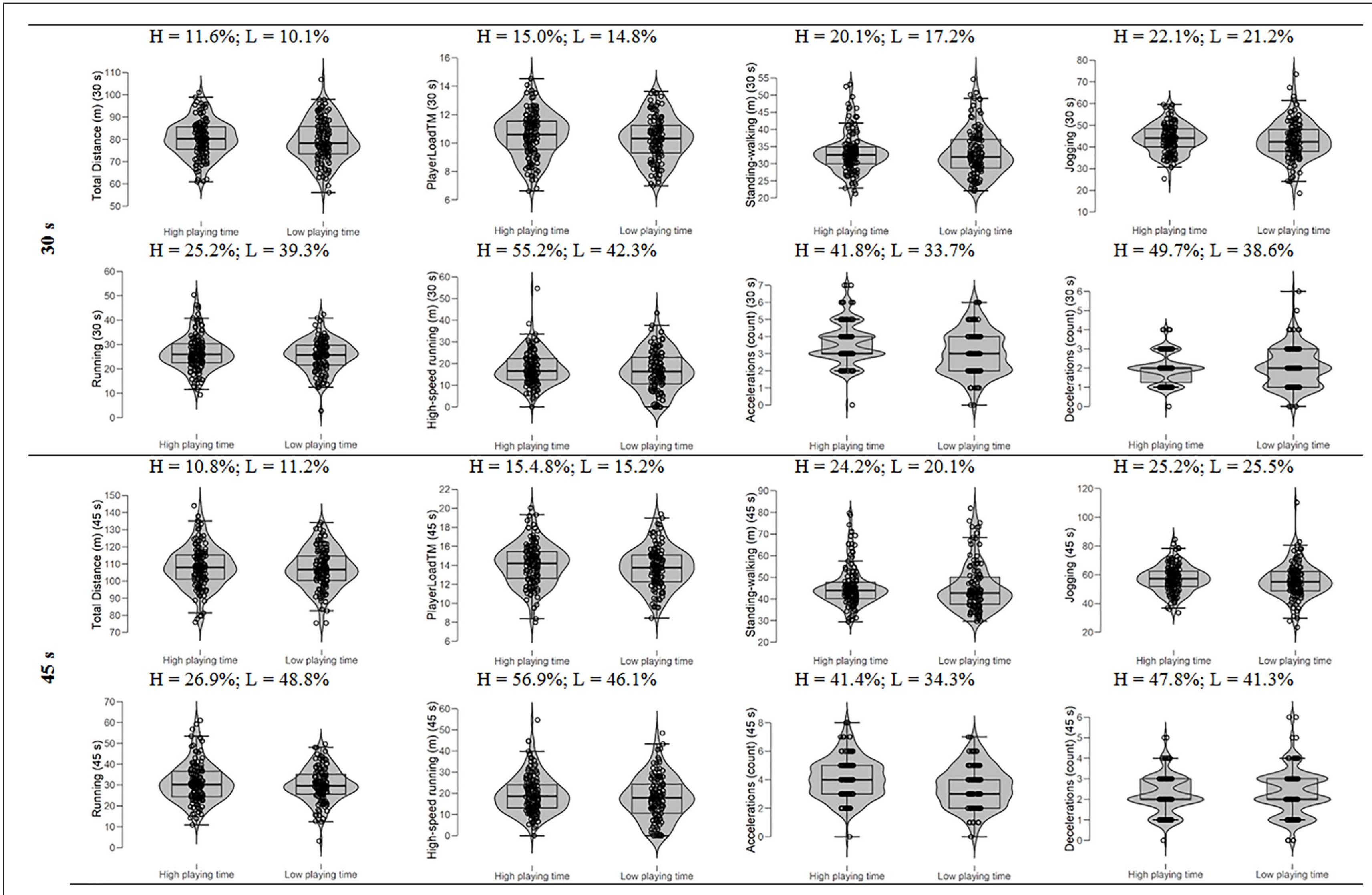

Figure 1. *(continued)*

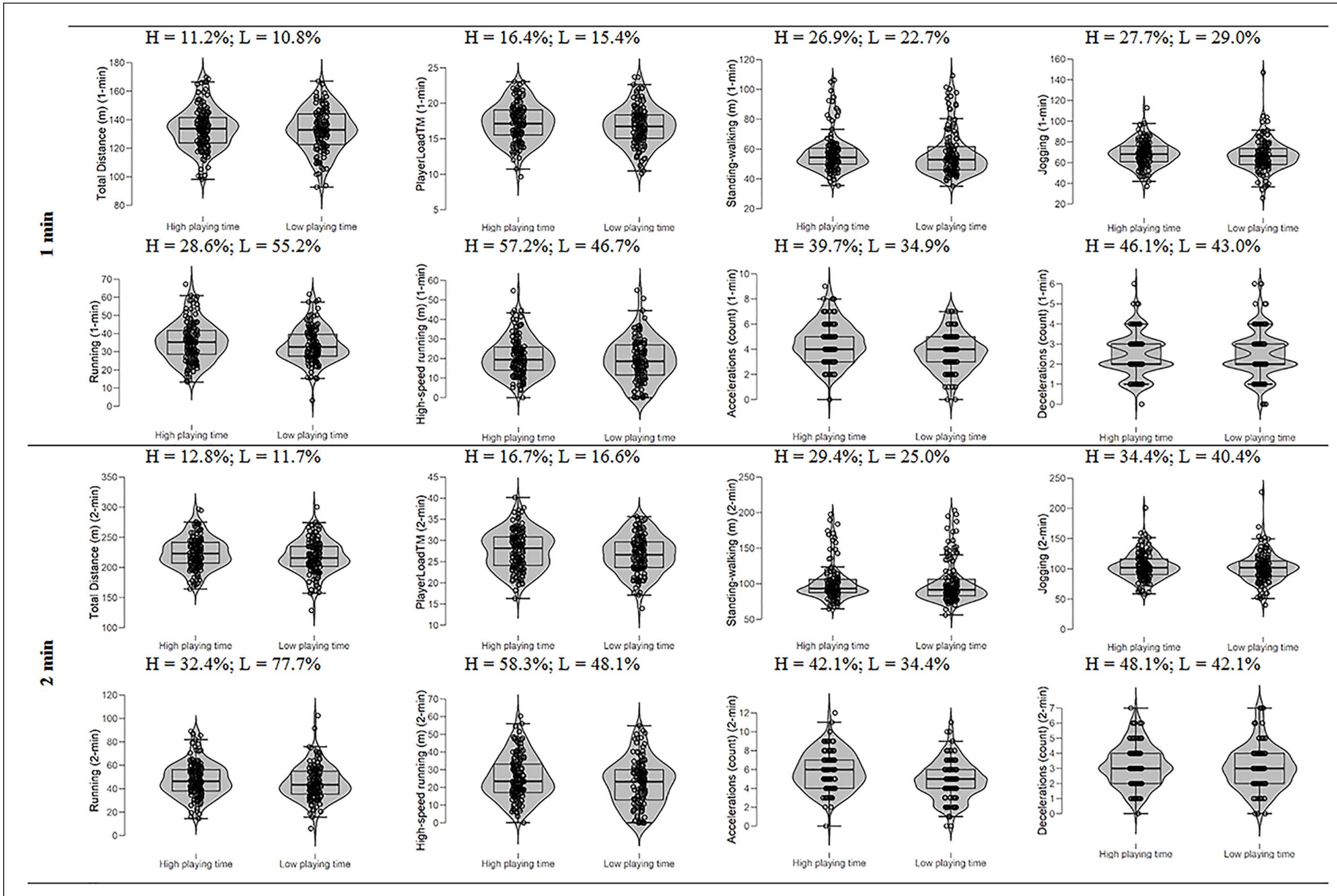

Figure 1. *(continued)*

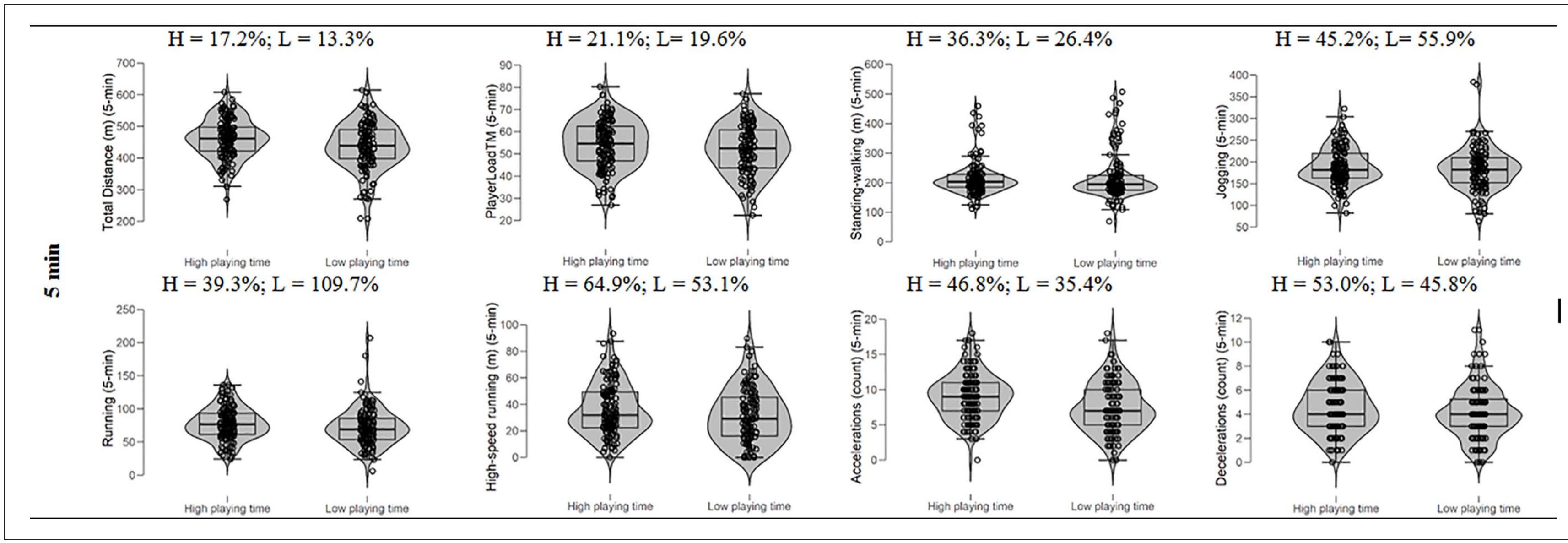

Figure 1. Descriptive analysis for groups according to total playing time during games for each external peak demand variable across different time windows.
Note. % values represent the coefficient of variation (CV%) for each group. H = high playing time, L = low playing time.

Table 4. Differences in External Peak Demands Between High and Low Total Playing Time Groups.

Variable	Time Window	*p* Value	Effect Size [95% CI]	Effect Size Magnitude	Mean Difference [95% CI]
Total distance (m)	30 s	0.329	–0.12 [–0.36, 0.12]	Trivial	–1.03 [–3.10, 1.04]
	45 s	0.524	–0.08 [–0.32, 0.16]	Trivial	–0.92 [–3.76, 1.92]
	1 min	0.472	–0.09 [–0.33, 0.15]	Trivial	–1.28 [–4.78, 2.22]
	2 min	0.055	–0.23 [–0.47, 0.01]	Small	–6.31 [–12.76, 0.14]
	5 min	0.004*	–0.35 [–0.59, –0.11]	Small	–23.88* [–40.16, –7.61]
PlayerLoad	30 s	0.166	–0.17 [–0.41, 0.07]	Trivial	–0.26 [–0.64, 0.11]
	45 s	0.524	–0.21 [–0.45, 0.03]	Small	–0.92 [–3.76, 1.92]
	1 min	0.147	–0.18 [–0.42, 0.06]	Trivial	–0.48 [–1.12, 0.17]
	2 min	0.066	–0.23 [–0.46, 0.02]	Small	–1.02 [–2.10, 0.07]
	5 min	0.073	–0.22 [–0.46, 0.02]	Small	–2.36 [–4.94, 0.22]
Standing-walking distance (m)	30 s	0.847	–0.02 [–0.26, 0.21]	Trivial	–0.15 [–1.62, 1.33]
	45 s	0.887	–0.02 [–0.26, 0.22]	Trivial	–0.17 [–2.57, 2.23]
	1 min	0.951	–0.01 [–0.25, 0.23]	Trivial	–0.11 [–3.49, 3.28]
	2 min	0.835	0.03 [–0.21, 0.26]	Trivial	0.70 [–5.87, 7.26]
	5 min	0.551	0.07 [–0.17, 0.31]	Trivial	4.96 [–11.38, 21.30]
Jogging distance (m)	30 s	0.318	–0.12 [–0.36, 0.12]	Trivial	–1.17 [–3.46, 1.13]
	45 s	0.241	–0.14 [–0.38, 0.10]	Trivial	–2.09 [–5.60, 1.42]
	1 min	0.253	–0.14 [–0.38, 0.10]	Trivial	–2.76 [–7.51, 1.99]
	2 min	0.375	–0.11 [–0.35, 0.13]	Trivial	–4.38 [–14.07, 5.31]
	5 min	0.325	–0.12 [–0.36, 0.12]	Trivial	–12.23 [–36.63, 12.16]
Running distance (m)	30 s	0.080	–0.21 [–0.45, 0.03]	Small	–1.91 [–4.04, 0.23]
	45 s	0.160	0.54 [0.29, 0.78]	Small	–2.17 [–5.21, 0.86]
	1 min	0.094	–0.20 [–0.44, 0.04]	Small	–3.31 [–7.18, 0.56]
	2 min	0.109	–0.20 [–0.43, 0.04]	Small	–5.94 [–13.22, 1.34]
	5 min	0.134	–0.18 [–0.42, 0.06]	Trivial	–12.86 [–29.72, 3.99]
High-speed running distance (m)	30 s	0.318	–0.12 [–0.36, 0.12]	Trivial	–1.01 [–3.00, 0.98]
	45 s	0.173	–0.17 [–0.41, 0.07]	Trivial	–1.59 [–3.87, 0.70]
	1 min	0.166	–0.17 [–0.41, 0.07]	Trivial	–1.74 [–4.20, 0.73]
	2 min	0.044*	–0.25 [–0.49, 0.01]	Small	–3.10* [–6.13, –0.09]
	5 min	0.060	–0.23 [–0.47, 0.01]	Small	–4.53 [–9.26, 0.20]
Accelerations (count)	30 s	<0.001*	–0.48 [–0.72, –0.23]	Small	–0.58* [–0.89, –0.29]
	45 s	<0.001*	–0.45 [–0.69, –0.21]	Small	–0.63* [–0.98, –0.30]
	1 min	<0.001*	–0.49 [–0.73, –0.25]	Small	–0.75* [–1.12, –0.39]
	2 min	<0.001*	–0.49 [–0.73, –0.25]	Small	–0.98* [–1.47, –0.50]
	5 min	<0.001*	–0.47 [–0.71, –0.22]	Small	–1.56* [–2.36, –0.76]
Decelerations (count)	30 s	0.617	0.06 [–0.18, 0.29]	Trivial	0.05 [–0.16, 0.27]
	45 s	0.341	0.12 [–0.12, 0.36]	Trivial	0.12 [–0.13, 0.36]
	1 min	0.771	0.04 [–0.20, 0.28]	Trivial	0.04 [–0.22, 0.30]
	2 min	0.394	–0.10 [–0.34, 0.14]	Trivial	–0.14 [–0.48, 0.19]
	5 min	0.192	–0.16 [–0.40, 0.08]	Trivial	–0.34 [–0.85, 0.17]

Note. Comparisons are between high and low total playing time groups. Statistical significance was set at an alpha level of <.05 (*).CI = confidence intervals.

accomplished greater PD for total distance (F = 7.24, p = .01, small) and PL (F = 6.08, p = .01, small) compared to the high prior playing time group. Across 2-min time windows, there was a significant group effect in PD for total distance (F = 7.06, $p < .001$) and PL (F = 6.17, $p < .001$). Post hoc analyses showed the low prior playing time group accomplished higher PD for total distance than the low-medium (p = .002, small), medium-high (p = .04, small), and high ($p < .001$, moderate) prior playing time groups, and for PL than the low-medium (p = 0.006, small), medium-high (p = .04, small), and high ($p < .001$, moderate) prior playing time groups. Across 5-min time windows, the low prior playing time group attained significantly higher PD for HSR distance (F = 10.44, $p < .001$, small) compared to the high prior playing time group.

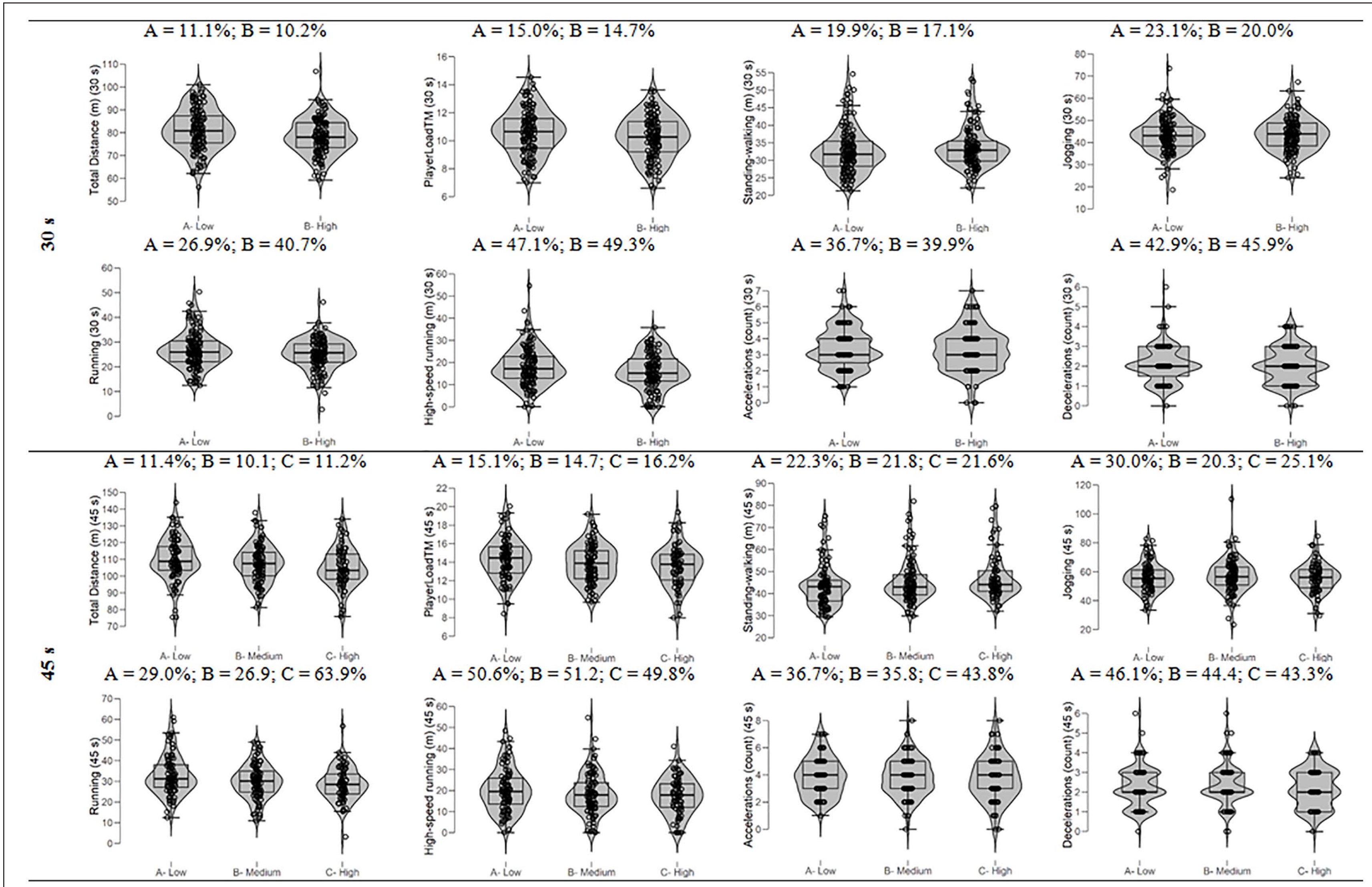

Figure 2. *(continued)*

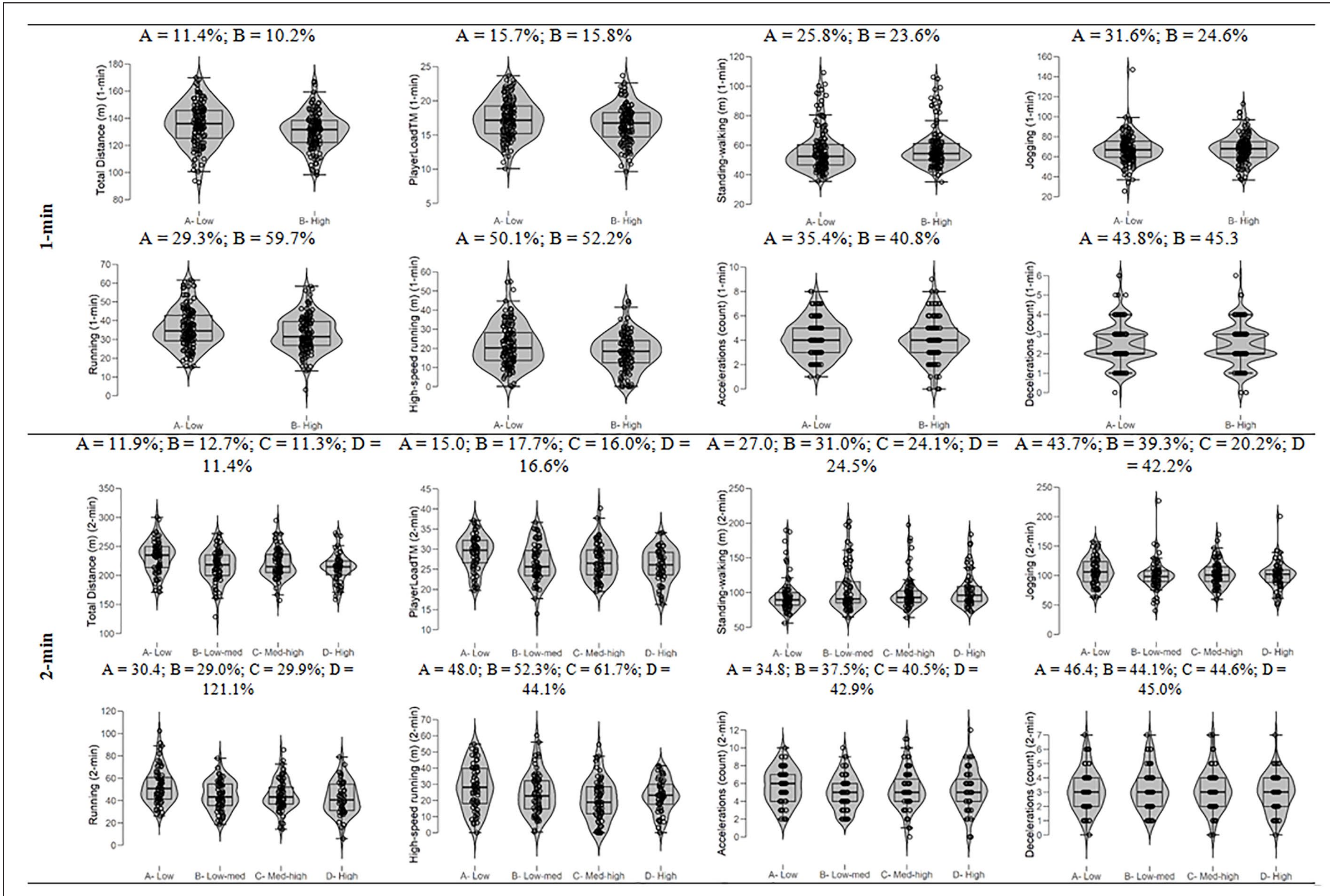

Figure 2. *(continued)*

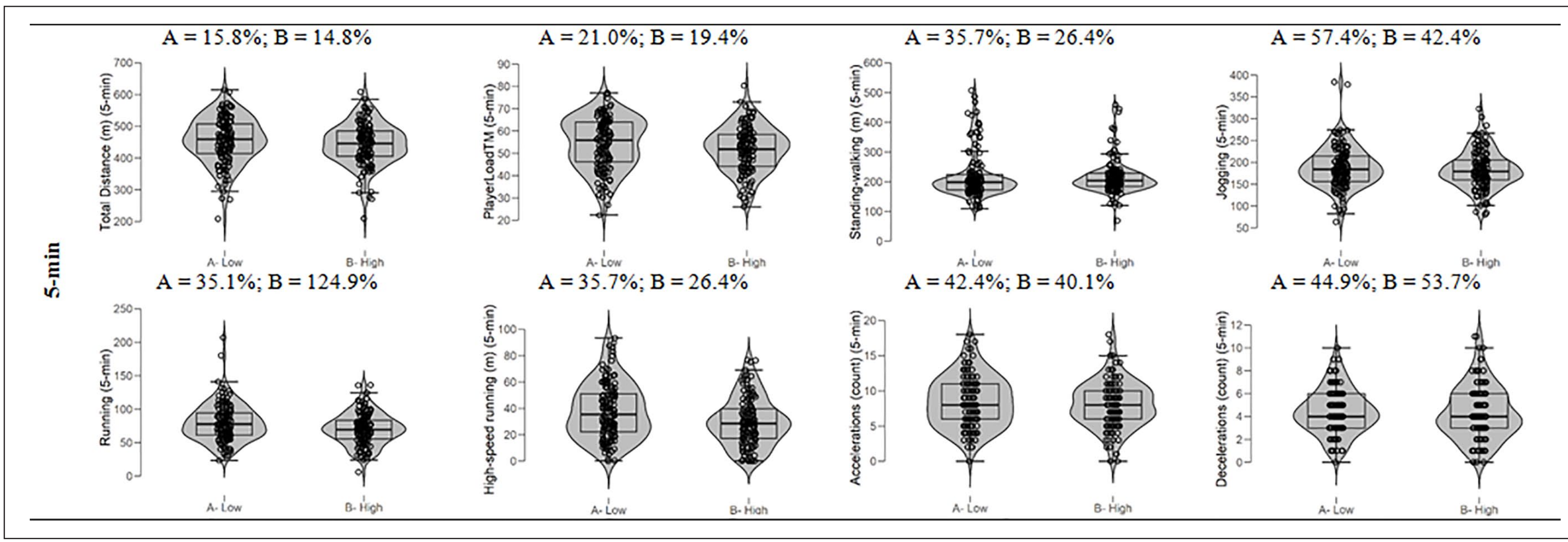

Figure 2. Descriptive analysis for groups according to prior playing time before peak demand episodes for each external peak demand variable across different time windows.
Note. % values represent the coefficient of variation (CV%) for each group. For 30-s, 1-min, and 5-min time windows, A = low prior playing time and B = high prior playing time). For 45-s time windows, A = low prior playing time, B = medium prior playing time, and C = high prior playing time. For 2-min time windows, A = low prior playing time, B = low-medium prior playing time, C = medium-high prior playing time, and D = high prior playing time.

Discussion

The aim of this study was to analyze the effects of playing time on the external PD experienced during basketball games. Specifically, the effects of (1) total playing time during games and (2) playing time accumulated directly prior to each external PD episode were examined. The present study provides impactful findings for basketball coaches and performance staff, demonstrating that higher external PD are reached by players who complete less total playing time and accumulate lower playing times before each PD episode during games.

Comparisons in external PD between players according to total game playing time showed players who completed less playing time (group means: 16 min vs. 25 min) were able to execute more intense accelerations >2 m·s^{-2} across 30-s to 5-min windows, as well as cover more total distance across a 5-min window and HSR distance across a 2-min window. These findings may be attributed to players completing lower playing times during games being less fatigued than players completing more playing time, with associated fatigue mechanisms reducing the ability to produce a given force or power output (Gibson & Noakes, 2004; Green, 1997). For instance, glycogen depletion, muscle damage, action potential interruption, and excitation-contraction coupling failure (Gibson & Noakes, 2004; Green, 1997; Noakes et al., 2005) resulting from basketball activity may impede the ability of players to sustain high-intensity activity outputs across different time windows (Green, 1997). In this regard, accelerations were greater with less total playing time accrued across all time windows suggesting rapid accelerative ability may be a particularly sensitive movement that deteriorates with greater playing time during games. This finding is particularly impactful for game situations given accelerations are readily performed by players when transitioning up and down the court (e.g., following turnovers, fast breaks, changes in possession) and during explosive cutting maneuvers to create open space when on offence and staying near opponents when on defense. In addition to accelerations, the reduced PD for total and HSR distance across longer windows could indicate brief intense running loads are not impacted by playing time, but continuous intense running loads accumulated >2 min are reduced with more playing time during games. These findings may help inform coaches when making strategic decisions during games (i.e., substitutions or time-outs to manage individualized playing time) that enable players to attain high external loads during crucial passages of play.

Our findings contrast those reported in past basketball research where the PD for PL were elevated in starting, semi-professional, male players ($p > .05$, moderate) who completed greater total playing times compared to bench players during games (mean playing time: 33.2 $\pm$ 1.2 min vs. 8.7 $\pm$ 6.0 min) (Fox, Conte, et al., 2020). Reasons for variations between studies could relate to the grouping of starter and bench players in past work, which resulted in pronounced lower playing times being achieved by bench players compared to starters during games (Fox, Conte, et al., 2020). In this regard, it was likely difficult for bench players to attain high external loads across varying time windows, especially longer durations, given the lack of opportunity to execute repeated intense movements during active game sequences. In opposition, the present study grouped players according to playing time, producing a noticeably higher mean playing time in the low group than observed for the bench group in previous research (playing times for low playing time group in our study vs. bench group in previous research: 16.6 $\pm$ 2.4 min vs. 8.7 $\pm$ 6.0 min) (Fox, Conte, et al., 2020). Consequently, use of cluster analyses likely better isolates the impact of playing time rather than relying on player role (starter vs. bench players), emphasizing the novel insight offered from our findings. Nevertheless, comparisons across studies reporting PD for PL should be interpreted carefully given PL has demonstrated high variability between team sport athletes (Barrett et al., 2014).

Comparisons in external PD between players according to playing time accrued prior to each PD episode showed players who participated less underwent higher PD for total distance (30-s to 2-min windows), PL (1-min to 2-min windows), and HSR distance (30-s and 5-min windows) than players who participated more before each external PD episode during games. These outcomes suggest players cannot attain as high peak external demands when accumulating more playing leading into intense passages of player during games. The reduced PD with more playing time directly preceding intense passages of play may be attributed to fatigue-related mechanisms similar to those postulated for findings considering the total playing time of players. Alternatively, the fact that players with more playing time before each PD episode achieved lower peak activity outputs may have been influenced by non-fatigue-related factors. For example, the PD accomplished by players may depend on the team lineup used when they are active in the game due to variations in player capacities (Alonso et al., 2020), team cohesion, and tactical approaches, as well as the stage of the game in which they are competing (e.g., game pace may decline during latter periods) (Fox, Salazar, et al., 2020; García et al., 2020).

When interpreting the present findings, it is important to note that nonsignificant, trivial differences were found between players grouped according to total game playing time and playing time prior to each PD episode for several external PD variables across different time windows. These findings reinforce the importance of considering specific PD variables for different functions due to the specific insight they each provide. In addition, given that the external PD attained by basketball players is impacted by various factors including schedule congestion (Edwards et al., 2018), player position (Alonso et al., 2020; Vázquez-Guerrero & Garcia, 2020), and game score-line (Vázquez-Guerrero et al., 2020), the impact of individualized playing time should be considered in tandem with these other factors. Another notable finding in our study was the high CV% across PD variables suggesting wide variability in the data obtained across players. This variability might be attributed to several factors such as the different fitness capacities that can exist across players in the same team and the tactical roles adopted by different players. Consequently, each player should be treated uniquely, and "normal" PD values may be difficult to establish across basketball players during games in consideration of playing time.

Our findings offer useful practical translation in many ways for basketball coaches and performance staff. First, it may be useful to expose players to intense passages of play during simulated games toward the end of training sessions to best prepare them to endure external PD episodes in fatigued states during games. Second, the heightened external PD with reduced playing time should be considered during return-to-play processes when playing time during games is progressively increased in players to reach that typical of the pre-injured state. In this way, it is essential to ensure players returning from injury are adequately prepared to cope with the external PD likely to be experienced in light of the playing time they accumulate. Third, these findings can be used to inform tactical coaching decisions where the playing time of players may be managed (e.g., substitutions, time-outs) to allow them to accomplish high external loads when desired during gameplay.

The limitations encountered in completing this study should be considered when interpreting our results. First, external PD across 5-min windows are likely to encompass time-outs given the regularity at which they are taken by coaches during game quarters. Nevertheless, external PD provided across 5-min windows provide valuable insight given this duration is commonly implemented when prescribing various drills during training scenarios. Second, fatigue markers (e.g., internal responses such as heart rate variability and perceptual responses such as wellness and readiness) were not measured in our study and were identified as potential mechanistic variables to explain our findings. Consequently, future research should include a suite of external and internal load variables when quantifying PD in basketball players during games to provide a more comprehensive understanding of player demands. Finally, the sample size we employed was small, given that it was indicative of a single elite, junior, male basketball team. In turn, further research is needed to identify if our findings hold consistent in other teams across wider samples of basketball players encompassing male and female players.

Conclusions

The present study provides novel findings that are useful for basketball coaches and performance staff, showing players who undertake less playing time can reach higher peak external loads aggregated across varied time windows during basketball games. Players categorized as completing a lower total playing time during games and prior to each PD episode were likely less fatigated and thus more prepared to accomplish higher external loads (i.e., total distance, PL, HSR distance, and accelerations) than players completing higher total playing times during games and prior to each PD episode. In turn, these findings present valuable insight to guide training prescription and player management during games to optimize player performance.

Declaration of Conflicting Interests

The author(s) declared no potential conflicts of interest with respect to the research, authorship, and/or publication of this article.

Funding

The author(s) received no financial support for the research, authorship, and/or publication of this article.

ORCID iD

Enrique Alonso Pérez-Chao https://orcid.org/0000-0002-8678-8702

References

Abdelkrim, N. Ben, El Fazaa, S., & El Ati, J. (2007). time-motion analysis and physiological data of elite under-19-year-old basketball players during competition. *British Journal of Sports Medicine*, *41*(2), 69–75.

Alonso, E., Miranda, N., Zhang, S., Sosa, C., Trapero, J., Lorenzo, J., & Lorenzo, A. (2020). Peak match demands in young basketball players: Approach and applications. *International Journal of Environmental Research and Public Health*, *17*(7), 2256.

Barrett, S., Midgley, A., & Lovell, R. (2014). PlayerLoad ™: Reliability, convergent validity and influence of unit position during treadmill running. *International Journal of Sports Physiology and Performance*, *9*(6), 945–952.

Brown, W., & Greig, M. (2015). Research report: Tri-axial accelerometry as an injury predictor tool in elite soccer. *International Journal of Athletic Therapy and Training*, *22*(5), 44–48.

Castellano, J., Casamichana, D., Calleja-González, J., Román, J. S., & Ostojic, S. M. (2011). Reliability and accuracy of

10 Hz GPS devices for short-distance exercise. *Journal of Sports Science and Medicine*, *10*(1), 233–234.

Chambers, R., Gabbett, T. J., Cole, M. H., & Beard, A. (2015). The use of wearable microsensors to quantify sport-specific movements. *Sports Medicine*, *45*(7), 1065–1081. https://doi.org/10.1007/s40279-015-0332-9

Cunningham, D. J., Shearer, D. A., Carter, N., Drawer, S., Pollard, B., Bennett, M., Eager, R., Cook, C. J., Farrell, J., Russell, M., & Kilduff, L. P. (2018). Assessing worst case scenarios in movement demands derived from global positioning systems during international rugby union matches: Rolling averages versus fixed length epochs. *PLoS ONE*, *13*(4), 1–14.

Edwards, T., Spiteri, T., Piggott, B., Bonhotal, J., Haff, G. G., & Joyce, C. (2018). Monitoring and managing fatigue in basketball. *Sports*, *6*(1), 19.

Fox, J. L., Conte, D., Stanton, R., McLean, B., & Scanlan, A. T. (2020). The application of accelerometer-derived moving averages to quantify peak demands in basketball. *Journal of Strength and Conditioning Research*. Advance online publication. https://doi.org/10.1519/jsc.0000000000003486

Fox, J. L., Salazar, H., García, F., & Scanlan, A. (2020). Peak external intensity decreases across quarters during basketball games. *Montenegrin Journal of Sports Science and Medicine*, *8*(2), 5–12.

Gabbett, T. J. (2013). Quantifying the physical demands of collision sports: Does microsensor technology measure what it claims to measure? *Journal of Strength and Conditioning Research*, *27*(8), 2319–2322.

García, F., Vázquez-Guerrero, J., Castellano, J., Casals, M., & Schelling, X. (2020). Physical demands between game quarters and playing positions on professional basketball players during official competition. *Journal of Sports Science and Medicine*, 19, 256–263.

Gibson, C., & Noakes, T. D. (2004). Evidence for complex system integration and dynamic neural regulation of skeletal muscle recruitment during exercise in humans. *British Journal of Sports Medicine*, *38*(6), 797–806.

Gómez Carmona, C. D., Bastida-Castillo, A., García-Rubio, J., Pino-Ortega, J., & Ibáñez, S. J. (2019). Game outcome influence in external load demands in youth male basketball during official competition. *Cuadernos de Psicologia Del Deporte*, *19*(1), 262–274.

Green, H. J. (1997). Mechanisms of muscle fatigue in intense exercise. *Journal of Sports Sciences*, *15*(3), 247–256.

Harriss, D. J., & Atkinson, G. (2014). Ethical standards in sport and exercise science research: 2014 update. *International Journal Sports Medicine*, *34*, 1025–1029.

Hellmann, F., Verdi, M., Schlemper Junior, B. R., & Caponi, S. (2014). 50th anniversary of the declaration of helsinki: The double standard was introduced. *Archives of Medical Research*, *45*(7), 600–601.

Hodder, R. W., Ball, K. A., & Serpiello, F. R. (2020). Criterion validity of catapult clearsky t6 local positioning system for measuring inter-unit distance. *Sensors*, *20*(13), 3693.

Hopkins, W. G., Marshall, S. W., Batterham, A. M., & Hanin, J. (2009). Progressive statistics for studies in sports medicine and exercise science. *Medicine and Science in Sports and Exercise*, *41*(1), 3–12.

Hoppe, M. W., Baumgart, C., Polglaze, T., & Freiwald, J. (2018). Validity and reliability of GPS and LPS for measuring distances covered and sprint mechanical properties in team sports. *PLoS ONE*, *13*(2), e0192708.

Johnston, R. J., Watsford, M. L., Kelly, S. J., Pine, M. J., & Spurrs, R. W. (2014). Validity and interunit reliability of 10 hz and 15 hz GPS units for assessing athlete movement demands. *Journal of Strength and Conditioning Research*, *28*(6), 1649–1655.

Luteberget, L. S., Spencer, M., & Gilgien, M. (2018). Validity of the catapult ClearSky T6 local positioning system for team sports specific drills, in indoor conditions. *Frontiers in Physiology*, *9*, 115.

Montgomery, P. G., Pyne, D. B., & Minahan, C. L. (2010). The physical and physiological demands of basketball training and competition. *International Journal of Sports Physiology and Performance*, *5*(1), 75–86.

Nicolella, D. P., Torres-Ronda, L., Saylor, K. J., & Schelling, X. (2018). Validity and reliability of an accelerometer-based player tracking device. *PLoS ONE*, *13*(2), 1–13.

Noakes, T. D., Gibson, C., & Lambert, E. V. (2005). From catastrophe to complexity: A novel model of integrative central neural regulation of effort and fatigue during exercise in humans: Summary and conclusions. *British Journal of Sports Medicine*, *39*(2), 120–124.

O'grady, C. J., Dalbo, V. J., Teramoto, M., Fox, J. L., & Scanlan, A. T. (2020). External workload can be anticipated during 5 vs. 5 games-based drills in basketball players: An exploratory study. *International Journal of Environmental Research and Public Health*, *17*(6), 2013.

Oliva-lozano, A. J. M., Martín-fuentes, I., Fortes, V., & Muyor, J. M. (2020). Differences in worst-case scenarios calculated by fixed length and rolling average methods in professional soccer match-play. *Biology of Sport*, *38*(3), 325–331.

Phillips, R. O. (2015). A review of definitions of fatigue and a step towards a whole definition. *Transportation Research Part F: Traffic Psychology and Behaviour*, *29*, 48–56.

Pino-Ortega, J., Rojas-Valverde, D., Gómez-Carmona, C. D., Bastida-Castillo, A., Hernández-Belmonte, A., García-Rubio, J., Nakamura, F. Y., & Ibáñez, S. J. (2019). Impact of contextual factors on external load during a congested-fixture tournament in Elite U'18 basketball players. *Frontiers in Psychology*, 10, 1100.

Puente, C., Abian, J., Areces, F., Lopez, R., & Coso, J. Del. (2016). Physical and physiological demands of experienced male basketball players during a competitive game. *Journal of Strength and Conditioning Research*, *31*(4), 956–962.

Serpiello, F. R., Hopkins, W. G., Barnes, S., Tavrou, J., Duthie, G. M., Aughey, R. J., & Ball, K. (2018). Validity of an ultra-wideband local positioning system to measure locomotion in indoor sports. *Journal of Sports Sciences*, *36*(15), 1727–1733.

Sosa, C., Lorenzo, A., Trapero, J., Ribas, C., Alonso, E., & Jimenez, S. L. (2021). Specific absolute velocity thresholds during male basketball games using local positional system ; differences between age categories. *Applied Sciences*, *11*(10), 4390.

Stojanović, E., Stojiljković, N., Scanlan, A. T., Dalbo, V. J., Berkelmans, D. M., & Milanović, Z. (2018). The activity demands and physiological responses encountered during basketball match-play: A systematic review. *Sports Medicine*, *48*(1), 111–135.

Vázquez-Guerrero, J., Ayala, F., Garcia, F., & Sampaio, J. (2020). The most demanding scenarios of play in basketball competition from elite under-18 teams. *Frontiers in Psychology*, *11*, 552.

Vázquez-Guerrero, J., & Garcia, F. (In press). Is it enough to use the traditional approach based on average values for basketball physical performance analysis? *European Journal of Sport Science*, *0*(0), 1–18.