International Journal of Performance Analysis in Sport

ISSN: 2474-8668 (Print) 1474-8185 (Online) Journal homepage: www.tandfonline.com/journals/rpan20

Analysing elite European basketball players' performances according to travel demands, game schedule and contextual factors

Pierpaolo Sansone, Daniele Conte, Lorenzo Gasperi, Aaron T. Scanlan & Miguel Angel Gomez-Ruano

To cite this article: Pierpaolo Sansone, Daniele Conte, Lorenzo Gasperi, Aaron T. Scanlan & Miguel Angel Gomez-Ruano (2025) Analysing elite European basketball players' performances according to travel demands, game schedule and contextual factors, International Journal of Performance Analysis in Sport, 25:3, 446-461, DOI: 10.1080/24748668.2024.2418185

To link to this article: https://doi.org/10.1080/24748668.2024.2418185

Published online: 19 Oct 2024.

Submit your article to this journal

Article views: 194

View related articles

View Crossmark data

Citing articles: 5 View citing articles

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=rpan20

INTERNATIONAL JOURNAL OF PERFORMANCE ANALYSIS IN SPORT
2025, VOL. 25, NO. 3, 446–461
https://doi.org/10.1080/24748668.2024.2418185

Analysing elite European basketball players' performances according to travel demands, game schedule and contextual factors

Pierpaolo Sansone [a,b], Daniele Conte [a], Lorenzo Gasperi [c], Aaron T. Scanlan [d] and Miguel Angel Gomez-Ruano [c]

[a]Department of Movement, Human and Health Sciences, University of Rome "Foro Italico", Rome, Italy; [b]UCAM Research Center for High Performance Sport, UCAM Universidad Católica de Murcia, Murcia, Spain; [c]Facultad de Ciencias de La Actividad Física y Del Deporte, Universidad Politécnica de Madrid, Madrid, Spain; [d]School of Health, Medical and Applied Sciences, Central Queensland University, Rockhampton, Queensland, Australia

ABSTRACT

This study evaluated the effects of travel demands, scheduling, and contextual factors on individual player performances in the top 10 European basketball teams across the 2020–2021 season. Game-related statistics were analysed (n = 8,824 observations). Players were categorized into high, medium, and low status according to their average playing times. Hierarchical regression models evaluated the effects of distance travelled, hours since the previous game, contextual factors for the prior and current game, and playing position on performance indicators. Medium-status players collected fewer defensive rebounds (p = 0.009) and committed fewer fouls (p = 0.026), with more time between games. Further travelled distances were associated with reduced defensive rebounds (p = 0.017), alongside increased turnovers (p = 0.038) and 3-point shooting percentage (p = 0.032) in high-status players. After facing higher-level teams, high- and low-status players' shooting worsened (p<0.05). Guards excelled in free-throw shooting and assists, forwards had fewer turnovers, and centers had better 2-point shooting and rebounds.

ARTICLE HISTORY
Received 25 June 2024
Accepted 8 October 2024

KEYWORDS
Euroleague; performance analysis; fixture congestion; situational factors; team sports

1. Introduction

Understanding players' performance is one of the main goals for basketball coaches, scientists and data analysts. In fact, the analysis of players' technical and tactical performance during games can provide useful insights to design and update playbooks and appropriate strategies for upcoming games. This argument applies particularly in elite basketball competitions where winning or losing games play a key role in coaches' and players' careers.

The Euroleague is the top men's professional European club basketball league played by the best 18 European teams and is broadly considered to be the second highest basketball league in the world after the National Basketball Association (NBA). The

CONTACT Pierpaolo Sansone ppsansone@gmail.com Department of Movement, Human and Health Sciences, University of Rome "Foro Italico", Piazza Lauro de Bosis, Rome, Italy

© 2024 Cardiff Metropolitan University

season schedule features 612 games (34 games per team) during the in-season phase (from October to April) with a possible additional 9 more games (2 for play-in, 5 for play-off and 2 for the final four) if reaching the last stages of the competition (as per the 2023–2024 season). Generally, each team plays 1–2 Euroleague games and 1 national league game per week, resulting in congested game schedules. Playing several games in close succession has been shown to have negative impacts on physiological responses and well-being in basketball players (Conte et al., 2021). This effect might also negatively influence teams' and players' technical and tactical performances. In fact, previous research investigating the effect of playing games in close succession in the NBA, which presents extremely high schedule congestion (82 games played over 26 weeks during the in-season phase), showed a lower likelihood of winning in back-to-back games (i.e. 0 rest days between games) compared to having 1 rest day between games (Esteves et al., 2021). Furthermore, Yang et al. (2021) showed that NBA teams were scoring more in the paint and behind the three-point line in games separated by 1 and 2 days of rest compared to games played in a back-to-back fashion (i.e. 0 rest days between games). Collectively, these studies indicate a negative influence of playing congested game schedules on shooting performance among NBA teams. Interestingly, different results were shown when considering individual players' performances measured via game-related statistics during the Euroleague 2014–2015 and 2015–2016 in-season phases with the distance travelled and the number of rest days between games exerting no notable influences (Mateus et al., 2020). It should be considered that these variations in findings across studies for the Euroleague (Mateus et al., 2020) and NBA (Yang et al., 2021) might be due to lower schedule congestion in the Euroleague across the investigated in-season period (10 games played by each participating team between October and December resulting in ~1 weekly game). Considering these previous data for the Euroleague were collected in players several years ago, the higher schedule congestion and consequently total distance travelled during more recent Euroleague seasons necessitates an updated analysis on the effect of these factors on players' performances.

Analysis of the possible influence of schedule congestion and distance travelled might provide useful insight for basketball coaches, sport scientists and data analysts to optimise players' performance. Nevertheless, it should be noted that basketball is a situational sport encompassing several more contextual factors able to impact players' performance. Studies analysing Euroleague team performances showed an impact of the final score on game-related statistics during the 2016–2017 season with shooting percentage, steals and committed fouls differentiating between winners and losers in close games (i.e. score difference lower than 10 points), while other game-related statistics can be considered key performance indicators in balanced (10–21 points difference in score) and unbalanced (>21-point difference in score) games, such as 2-point field goals made and defensive rebounds (Çene, 2018). When considering individual performances, Sampaio et al. (2008) showed an effect of game location (home vs. away) on players' performance across various playing positions (guards, forwards and centres) during the 2004–2005 Euroleague season. Specifically, the game-related statistics which were better at home than away games were two-point shots, defensive rebounds, assists, steals, blocks and committed fouls for guards, while successful free-throws, assists, steals, blocks and committed fouls discriminated home and away games for forwards (Sampaio et al., 2008). However, to the best of the authors' knowledge, no previous studies assessed the effect of additional contextual variables on individual players' performance in the Euroleague such as the opponent level or factors related to the previous game played such as the playing time, outcome and opponent level, which have been shown to impact player performance in other top basketball leagues such as the NBA (Yang et al., 2021; Zhang et al., 2018). Consequently, there is a need to investigate the effect of various contextual factors in combination with travel demands and schedule congestion to generate comprehensive evidence concerning elements that may impact players' performances in the Euroleague. Therefore, this study aimed to evaluate the effects of travel demands, schedule congestion and contextual factors on individual player performances across different player statuses in the top 10 European basketball teams during the 2020–2021 season.

2. Methods

The sample consisted of the individual performances of players belonging to the 10 teams with the best final rankings at the end of the Euroleague 2020–2021 basketball season. Players' individual game-related statistics from all games played for these teams in their respective national leagues and the Euroleague across all season phases (regular season, playoffs and finals) were retrieved. Altogether, the sample consisted of 8,824 individual game observations obtained across 761 games. This sample is substantially greater than the one provided by our power analysis, which indicated that a minimum of 274 observations were needed for a hierarchical regression model involving three blocks of factors with an estimated effect size of 0.15 and a statistical power of 0.80.

The following game-related statistics were gathered: points; 2-point shot percentage (2P%); 3-point shot percentage (3P%); free-throw percentage (1P%); offensive rebounds; defensive rebounds; assists; steals; turnovers; blocks; blocks against; fouls committed; fouls drawn; and Performance Index Rating (PIR) (Gasperi et al., 2023; Sansone et al., 2021), calculated using the following formula: (Points + Rebounds + Assists + Steals + Blocks + Fouls Drawn) – (Missed Field-Goals + Missed Free-Throws + Turnovers + Shots Rejected + Fouls Committed). To control for game exposure, game-related statistics were normalised according to playing times (Gasperi et al., 2023; Sansone et al., 2021). Data were publicly available and retrieved from the official websites of the national leagues of the teams included and the Euroleague competition.

The following factors were collected for each game: i) travel and scheduling factors: hours since the previous game – counted from the start time of the previous game to the start time of the current game; distance (km) travelled between the location of the current game and the location of the previous game, calculated by measuring distance in a straight line (km) between the geographical coordinates of the cities; ii) previous game factors: minutes played; league – national or Euroleague, including the seasonal phase as the regular season, playoffs, or finals; result – win or lose; score differential; opponent level based on the league ranking (win percentage) at the end of the season and classified by k-means cluster analysis as higher (i.e. better ranking), similar, or lower (i.e. worse ranking); and iii) current game factors: playing position as listed by each team, categorised as guards ($n = 77$ players), forwards ($n = 64$ players), or centers ($n = 38$ players) (Sansone et al., 2021; Svilar et al., 2018); league – national or Euroleague, including the seasonal phase as regular season, playoffs, or finals; game location – home or away; result – win or lose; score differential; and opponent level – based on the league ranking (win percentage) at the end of the season and classified by k-means cluster analysis as higher, similar or lower.

Statistical analysis was performed using Jamovi Project statistical software (version 2.3), with the α value set at 0.05. The player sample was divided into high, medium and low playing statuses (Calleja-González et al., 2023) according to the playing times registered during games (Mateus et al., 2015) using k-means cluster analysis (Mateus et al., 2015; Sansone et al., 2021). Hierarchical multiple linear regression models were calculated to assess the impact of travel demands, schedule congestion and contextual factors on individual players' game-related statistics. The performances of high-, medium- and low-status players were separately analysed. Hierarchical regression was performed in three steps, including: (1) travel and schedule factors – the number of hours since the last game and the distance travelled in the first regression block; (2) previous game factors – the playing time, outcome, point difference, opponent level and league of the previous game were inserted into the second regression block; (3) current game factors – playing position, outcome, score differential, opponent level, location and league of the current game in the third regression block. For each model, R^2, coefficients for each factor, p-values and 95% confidence intervals (CI) were determined. Effect sizes (ES) were computed as Cohen's f^2 and interpreted as: <0.02 = null effect; 0.02–0.14 = small effect; 0.15–0.34 = medium effect; and ≥ 0.35 = large effect (M. Á. Gómez et al., 2017).

3. Results

Table 1 presents the descriptive game-related statistics according to player status. Tables 2, 3 and 4 present the significant effects found for high-, medium- and low-status players, respectively. In summary, schedule congestion did not affect the performances of high-status players, while less time between games were associated with decreased defensive rebounds ($p = 0.009$) and fouls committed ($p = 0.026$) in medium-status players. Greater travelled distances between games were associated with worsened defensive rebounds ($p < 0.05$), turnovers ($p < 0.05$) and 2P% ($p < 0.05$) in high- and low-status players. Playing more minutes in the previous game was associated with better performances for high- (points, PIR, blocks against, and fouls committed), medium- (points), and low-status (PIR and assists) players (all $p < 0.05$). After games against higher-level teams, high- and low-status players had poorer 1P% and 2P%, respectively. The previous game outcome influenced fouls committed by high-status players ($p = 0.045$), and offensive ($p = 0.013$) and defensive ($p = 0.010$) rebounds in low-status players. Regarding the league and season phase, high-status players drew fewer fouls (p <0.001), and low-status players performed more assists ($p = 0.036$) following regular season games, while medium-status players collected more offensive rebounds (p <0.001) following final games. Across all statuses, playing positions were characterised by specific statistical variables, with guards having better 1P% and assists, forwards having fewer turnovers and centers having better 2P% and rebounds, while position-specific results for high-, medium- and low-status players are presented in

Table 1. Game-related statistics according to player status.

Statistical variable	High-status	Medium-status	Low-status
Points	0.46 ± 0.25	0.36 ± 0.36	0.28 ± 0.31
2-point shot percentage (%)	55.0 ± 29.8	53.9 ± 34.3	46.0 ± 39.8
3-point shot percentage (%)	37.6 ± 33.1	36.6 ± 35.8	32.5 ± 37.3
Free-throw percentage (%)	81.6 ± 29.9	77.3 ± 31.9	71.6 ± 32.5%
Offensive rebounds	0.03 ± 0.05	0.05 ± 0.08	0.04 ± 0.08
Defensive rebounds	0.11 ± 0.08	0.11 ± 0.14	0.11 ± 0.13
Assists	0.12 ± 0.11	0.06 ± 0.10	0.10 ± 0.12
Steals	0.04 ± 0.05	0.03 ± 0.05	0.04 ± 0.08
Turnovers	0.06 ± 0.06	0.05 ± 0.10	0.06 ± 0.10
Blocks	0.01 ± 0.02	0.02 ± 0.04	0.01 ± 0.04
Blocks against	0.01 ± 0.02	0.01 ± 0.02	0.01 ± 0.04
Fouls committed	0.09 ± 0.07	0.13 ± 0.26	0.13 ± 0.16
Fouls drawn	0.10 ± 0.09	0.07 ± 0.30	0.04 ± 0.09
Performance Index Rating	0.51 ± 0.35	0.34 ± 0.50	0.24 ± 0.48

All statistical variables are reported as counts or as a rating per minute of playing time except for 2-point, 3-point and free-throw shooting percentages.

Tables 2, 3 and 4. Wins were associated with better performances of high-status players in points (p= 0.014) and PIR (p <0.001), while game outcome was not associated with any variable in medium-status players. Low-status players had more offensive rebounds (p= 0.048) and blocks (p= 0.003) at home than away, while game location was not associated with performances of high- and medium-status players.

4. Discussions

This study evaluated individual basketball player performances across national and international leagues by considering travel demands, schedule congestion, contextual factors and the player status. The main findings were: (i) considering the low R^2 values (0.02–0.24), schedule congestion, travel demands and contextual factors explained only a minor part of individual player performances; (ii) high-status players could maintain their performances when faced with congested schedules, while medium-status players' defensive rebounds and fouls committed decreased with less rest between games; (iii) greater distances travelled between games negatively influenced low-status players' defensive rebounds, turnovers and 2P%; (iv) specific performance profiles were identified across playing positions, with guards excelling in free-throw accuracy and assists, forwards having fewer turnovers, and centres showing better 2P% and rebounds than other positions; and (v) low-status players benefitted from playing at home in regards to obtaining more offensive rebounds and blocks.

This study found that schedule congestion, travel demands and contextual factors had significant influences on individual performances of elite European male basketball players. However, the low R^2 values (0.02–0.24) and *small-medium* effects sizes require some consideration. These effect magnitudes of effects show how the factors considered in our models could explain only a limited portion of the players' performances. Therefore, basketball practitioners should also consider further aspects (i.e. technical-tactical constraints, physical attributes, in-game situational variables) when trying to explain and optimise basketball players' performances.

Table 2. Factors contributing significant effects for each statistical variable in high-status players.

Statistical variable	R^2	Effect size (f^2), interpretation	Factor	Coefficient	95% confidence intervals	p
Points	0.06	0.07, small	Minutes played in previous game	0.004	0.002 – 0.005	<0.001
			Current game score differential	0.002	0.001 – 0.003	0.011
			Current game outcome (win-loss)	0.051	0.010 – 0.091	0.014
2P%	0.03	0.03, small	Playing position (guard-center)	−9.603	−13.333 – −5.872	<0.001
3P%	0.02	0.03, small	Distance travelled	0.002	0.001 – 0.003	0.032
			Current game score differential	0.337	0.185 – 0.489	<0.001
1P%	0.03	0.03, small	Previous game score differential	−0.223	−0.375 – −0.071	0.004
			Previous game opponent level (same-higher)	5.729	0.558 – 10.900	0.011
			Playing position (guard-center)	6.907	2.256 – 11.289	0.008
			Current game league and phase	—	—	0.048
Offensive rebounds	0.24	0.31, medium	Playing position (guard-center)	−0.030	−0.037 – −0.022	<0.001
			Playing position (forward-center)	−0.058	−0.065 – −0.051	<0.001
			Current game score differential	−0.001	−0.001 – −30700	0.027
Defensive rebounds	0.14	0.16, medium	Distance travelled	−0.001	−0.001– −0.001	0.017
			Playing position (guard-center)	−0.041	−0.054 – −0.029	<0.001
			Current game score differential	0.001	0.001 – 0.001	<0.001
Assists	0.21	0.27, medium	Playing position (guard-center)	−0.024	−0.042 – −0.006	<0.001
			Playing position (forward-centre)	0.070	0.005 – 0.083	0.009
			Current game score differential	0.001	0.001 – 0.002	<0.001
Steals	0.05	0.06, small	Previous game opponent level (lower-higher)	0.013	0.001 – 0.026	0.040
			Playing position (forward-center)	−0.011	−0.020 – −0.002	0.017
			Current game score differential	−0.001	0.001 – 0.001	0.018
Turnovers	0.06	0.07, small	Distance travelled	−0.001	25200 – 0.001	0.038
			Minutes played in previous game	−0.001	0.001 – 0.001	0.036
			Playing position (forward-center)	−0.017	−0.028 – −0.006	0.002
			Current game score differential	−0.001	−0.001 – −0.001	0.041
Blocks	0.12	0.14, small	Playing position (guard-center)	−0.020	−0.023 – −0.016	<0.001
			Playing position (forward-center)	−0.009	−0.013 – −0.004	<0.001
Blocks against	0.05	0.05, small	Minutes played in previous game	−0.001	−0.001 – −0.001	0.039
			Playing position (forward-center)	−0.008	−0.012 – −0.003	0.005
Fouls committed	0.09	0.09, small	Minutes played in previous game	−0.001	−0.001 – −0.001	0.004

(*Continued*)

Table 2. (Continued).

Statistical variable	R^2	Effect size (f^2), interpretation	Factor	Coefficient	95% confidence intervals	p
			Previous game outcome (win-loss)	—	—	0.045
			Previous game opponent level (lower-higher)	0.024	0.007 – 0.041	0.006
			Previous game opponent level (same-higher)	0.024	0.005 – 0.042	0.012
			Playing position (guard-center)	−0.028	−0.039 – −0.018	<0.001
			Playing position (forward-center)	−0.041	−0.054 – −0.029	<0.001
			Current game league and phase	—	—	0.004
Fouls drawn	0.11	0.12, small	Previous game score differential	0.001	0.001 – 0.001	0.039
			Previous game league and phase	—	—	<0.001
			Playing position (guard-center)	−0.029	−0.044 – −0.014	<0.001
			Current game league and phase	—	—	<0.001
Performance Index Rating	0.12	0.13, small	Minutes played in previous game	0.004	0.002 – 0.007	0.002
			Playing position (guard-center)	−0.098	−0.055 – −0.040	<0.001
			Current game score differential	0.005	0.003 – 0.007	<0.001
			Current game outcome (win-loss)	0.096	0.039 – 0.153	<0.001

Dashes indicate coefficients with confidence intervals were not computed by the statistical software.

Game schedules can influence team training and preparation plans, and might therefore affect individual player performances. While a previous similar study in European basketball players did not find game schedule to significantly influence players' performances (Mateus et al., 2020), this study found that the time between games significantly influenced performance (some game-related statistics) in medium- and low-status players, but not high-status players. These results suggest that better players can maintain their performances despite experiencing schedule congestion and less time available to recover between games. Differently, medium-status players collected fewer defensive rebounds and committed less fouls when games were scheduled in closer proximity, while low-status players had poorer 3P% and drew fever fouls with less time between games. While these effects are significant, it is important to note that these factors explained only 2–4% of the associated game-related statistics, which may indicate that schedule congestion has limited practical consequences for game-related statistics in European basketball. In turn, the lack of effects observed – especially in high-status players – suggest that elite European basketball coaching staff may be optimally managing players across the season in a way that ensures individual performances are not affected when faced with more demanding schedules.

In elite basketball, travel demands are considerable and have been shown to affect team performance (Wang et al., 2023). Overall, greater travelled distances negatively influenced certain game-related statistics in this study. High-status players collected fewer defensive

Table 3. Factors contributing significant effects for each statistical variable in medium-status players.

Statistical variable	R^2	Effect size (f^2), interpretation	Factor	Coefficient	95% confidence intervals	p
Points	0.03	0.03, small	Minutes played in previous game	0.004	0.006 – 2.573	0.010
			Current game score differential	0.003	0.005 – 3.257	<0.001
2P%	0.03	0.04, small	Current game score differential	0.279	0.406 – 4.305	<0.001
			Playing position (guard-center)	−9.497	12.616 – −6.378	<0.001
			Playing position (forward-center)	−4.647	−7.676 – −1.617	0.003
3P%	0.02	0.03, small	Current game score differential	0.305	0.162 – 0.445	<0.001
1P%	0.03	0.03, small	Playing position (guard-center)	8.843	4.940 – 12.746	<0.001
			Current game league and phase	—	—	0.003
Offensive rebounds	0.14	0.17, medium	Previous game league and phase	—	—	<0.001
			Playing position (guard-center)	−0.077	−0.90 – −0.065	<0.001
			Playing position (forward-center)	−0.057	−0.068 – −0.047	<0.001
Defensive rebounds	0.04	0.05, small	Hours since previous game	−0.001	−0.001– −0.001	0.009
			Playing position (guard-center)	−0.068	−0.091 – −0.045	<0.001
Assists	0.04	0.05, small	Current game score differential	0.001	9.74e-5 – 0.001	0.020
			Playing position (guard-center)	0.046	0.030 – 0.061	<0.001
			Playing position (forward-center)	0.017	0.004 – 0.030	0.009
Turnovers	0.02	0.02, small	Hours since previous game	−0.001	−0.001– −0.001	0.033
Blocks	0.10	0.12, small	Playing position (guard-center)	−0.029	−0.034 – −0.023	<0.001
			Playing position (forward-center)	−0.021	−0.026 – 0.017	<0.001
Fouls committed	0.02	0.02, small	Hours since previous game	−0.001	−0.001 – −0.001	0.026
Performance Index Rating	0.04	0.04, small	Current game score differential	0.006	0.003 – 0.009	<0.001
			Playing position (guard-center)	−0.095	−0.175 – −0.015	0.020
			Playing position (forward-center)	−0.093	−0.161 – −0.024	0.009

Dashes indicate coefficients with confidence intervals were not computed by the statistical software.

rebounds and had more turnovers with increasing travel distances, while low-status players also suffered a decrease in 2P%. Importantly, the magnitudes of these effect were considerable, especially for defensive rebounds ($R^2 = 0.14$) and 2P% ($R^2 = 0.10$), which should therefore be considered by coaching staff when designing game plans. In contrast, only 3P% was improved – in high-status players – with increased travel. This result might be explained by an increased responsibility of higher-status players to take 3-point shots in games played away from home. Our findings disagree with a previous study that also analysed European national and Euroleague basketball competitions where travelled distance was shown to exert no significant effects on players' performances (Mateus et al., 2020). This discrepancy might be

Table 4. Factors contributing significant effects for each statistical variable in low-status players.

Statistical variable	R^2	Effect size (f^2), interpretation	Factor	Coefficient	95% confidence intervals	p
Points	0.14	0.16, medium	Minutes played in previous game	0.005	0.001 – 0.009	0.036
2P%	0.10	0.11, small	Distance travelled	−0.004	−0.008 – 0.001	0.018
			Previous game opponent level (lower-higher)	14.138	0.670 – 27.605	0.023
3P%	0.05	0.05, small	Hours since previous game	0.082	0.005 – 0.160	0.037
1P%	0.12	0.14, small	Current game league and phase	—	—	0.004
Offensive rebounds	0.16	0.19, medium	Previous game outcome (win-loss)	—	—	0.0013
			Playing position (guard-center)	—	—	<0.001
			Current game location (home-away)	0.018	0.001 – 0.036	0.048
Defensive rebounds	0.11	0.13, small	Previous game outcome (win-loss)	—	—	0.010
			Playing position (guard-centre)	—	—	0.018
Assists	0.21	0.26, medium	Minutes played in previous game	0.002	0.001 – 0.003	0.048
			Previous game league and phase	—	—	0.036
			Playing position (guard-center)	—	—	<0.001
Steals	0.11	0.12, small	Current game outcome (win-loss)	0.038	0.008 – 0.067	0.012
Turnovers	0.10	0.10, small	Current game outcome (win-loss)	0.048	0.009 – 0.087	0.016
Blocks	0.18	0.22, medium	Playing position (guard-center)	—	—	<0.001
			Current game location (home-away)	0.010	0.004 – 0.017	0.003
Fouls drawn	0.18	0.22, medium	Hours since previous game	−0.001	−0.001– −0.001	0.043
			Playing position (guard-forward)	—	—	0.015
			Current game league and phase	—	—	0.002
Performance Index Rating	0.15	0.18, medium	Minutes played in previous game	0.008	0.001– 0.015	0.035

Dashes indicate coefficients with confidence intervals were not computed by the statistical software.

due to the different seasons assessed, with our study analysing more recent seasons which have a more congested schedule and therefore different travel requirements compared to the seasons analysed by Mateus and colleagues (years 2014–2016), which featured only one game per week in each competition and therefore substantially lower travel demands. These findings suggest basketball coaches may need to modify tactical strategies (e.g. player rotations) or explore effective preparation strategies (e.g. recovery modalities) to compensate for the lower defensive rebounds and increased turnovers by high-status players during games following long travel, especially considering these variables are key performance indicators in basketball game-play (M. A. Gómez et al., 2008; Leicht et al., 2017).

Basketball performance staff carefully manage players' playing times according to the team's hierarchy, players' characteristics and game-related contextual factors while also trying to minimise fatigue. In this study, playing more minutes in the previous game was generally associated with better game-related statistics for high- (points, PIR, blocks against and fouls committed), medium- (points) and low-status (PIR and assists) players in the current game. These results agree with findings in a previous study examining European basketball players also competing in the Euroleague (Mateus et al., 2020) and highlight that within each cluster of players (determined via playing times), better players who are more productive on the court may inherently be involved more and substituted less during game-play. This trend may be a natural tendency led by the expertise of coaching staff who give more minutes to players who are likely to produce more positive performance indicators as shown via game-related statistics.

A recent study (Sansone et al., 2024, 2023) demonstrated that the opponent level faced in the previous game affects team statistics in the following game by possibly influencing team coordination dynamics and players' confidence. Our results for shooting performances partially confirm this notion, since high- and low-status players in this study had poorer 1P% and 2P%, respectively, after facing higher-level teams. Together with previous findings (Sansone et al., 2024, 2023), it can be suggested that shooting performances may be affected at both individual and team levels depending on the previous opponent faced. It is possible that, when facing higher-level opponents, the defensive pressure and higher physical (Koyama et al., 2024) and psychological demands of the game reduce players' confidence and/or elicit greater fatigue, which may have a carry-on effect to negatively impact shooting performances in the following game. These novel findings suggest basketball coaching staff should manipulate the time dedicated to shooting drills in training, especially increasing the focus on free-throw and 2-point shooting to ensure that accuracy is optimised after facing higher-level teams.

Similarly, the previous game score differential affected some current game performance indicators. More precisely, less balanced games, with higher score differentials between teams, are characterised by lower physical and physiological demands (Fox et al., 2019a) and reduced competitiveness. This scenario might lead to less stress being placed on players which enabled them to recovery more effectively and be better prepared for upcoming competition, where they obtained better 1P% and committed less fouls, as observed in this study. More precisely, a less balanced game posits less psychological stress, especially in specific situations such as free-throw shooting, which is characterised by greater difficulty during close games (M. Á. Gómez et al., 2018). In turn, players might be exposed to easier free-throw opportunities in such contexts, lessening the psychological toll and improving their confidence, which are beneficial to performance in the following game. Unbalanced games might be also characterised by lower physicality and intensity (Fox et al., 2019a), thus leading to players having better physical preparedness to accomplish defensive tasks, which may result in less fouls being committed in the following game. Nevertheless, the practical significance of these results for previous game score differential is more relevant for fouls committed, seen it explained 11% of the variance in players' fouls, while these effects were low for 1P% (3%).

In elite European basketball, players participate in both national and international leagues, which have been previously shown to have distinct performance profiles as shown by game-related statistics which also vary depending on the season phase (Sansone et al., 2024, 2023). In this study, high-status players drew less fouls and low-status players performed more assists in the game following regular season games, which may be perceived as having less importance and, therefore, possibly less demanding than playoff games, thus facilitating opportunities to perform assists while at the same time possibly involving lower defensive pressure from opponents. Indeed, tactical strategy changes according to the league and phase have been previously found within elite European basketball competitions, with diminished shooting performance and fouling during more decisive season phases (i.e. playoff and finals) (Sansone, et al., 2024, 2023). In fact, medium-status players collected more offensive rebounds after final games in this study, which might indicate an augmented effort to collect offensive rebounds stimulated during such important season phases. Current findings indicate that performance indicators in elite European basketball change across season phases, which should be well considered by coaches to improve the team's chances of success depending on the league and stage of competition. Specifically, team tactics should be adjusted during finals seen the augmented effort by opponents in collecting offensive rebounds Additionally, drills focused on team coordination dynamics might promote assists situations during games in key phases in which they appear to be less prominent.

The game outcome is possibly the most prominent aspect for practitioners in competitive sports. Our findings show that, following losses, players committed more fouls (high-status players) and collected more offensive and defensive rebounds (low-status players). Since losing is an unfavourable outcome, we hypothesise that players change their attitudes in the game following a loss by performing greater efforts to secure loose balls following missed shots which leads to more rebounds, and possibly showing more defensive aggressiveness leading to more fouls being committed. These results might also be attributed to an increased emphasis and focus in preparing for games following losses among coaching staff and players, considering rebounds are a key performance indicator for success in basketball teams (M. Á. Gómez et al., 2006; Leicht et al., 2017). Given these results explained 9–16% of the variance in fouls and rebounds, coaching staff may design training drills and emphasize, during pre-game and in-training speeches, the importance of controlling fouls and improving rebounding following losses, particularly given the importance of these game-related statistics for success (Çene, 2018; M. A. Gómez et al., 2008).

Basketball players' performances have been shown to differ across playing positions and roles (Gasperi et al., 2020; Sansone et al., 2021, Sansoneet al., 2023; Zhang et al., 2018). In this study, specific game-related statistics characterised player performances according to playing position and player status. Specifically, among high-status players, guards were characterised by better 1P%, and more assists, and steals, forwards committed less turnovers and had less of their shots blocked, while centers had better 2P% alongside more rebounds, blocks and fouls drawn than other positions. For medium-status players, guards had better 1P% and more assists, forwards had more defensive rebounds and assists, and centers had better 2P% and more points, offensive rebounds, and blocks. Regarding low-status players, guards had more assists and drew more fouls, forwards had more offensive rebounds, and centers had more blocks and offensive and defensive rebounds than other positions. These results corroborate previous research in confirming the importance of describing game performances according to the specific position and status of players (Gasperi et al., 2020; Lorenzo et al., 2019), to have more accurate expectations of players' potential performances which can ultimately favour the team's chances of success. Specifically, our findings suggest centres may capitalise on the greater body size they typically possess (Cui et al., 2019) to score closer to the basket with a high accuracy, rebound the ball, and block opponent shots. In turn, guards tend to hold responsibility for determining the team's offensive plays with extensive ball-handling to execute more assists, while the role of forward appears to be a hybrid of tasks demonstrating an importance on rebounding but also passing effectively to make assists (Delextrat et al., 2015; Sansone et al., 2021). These findings provide a specific profile for each of the major playing positions in elite European basketball, which coaches could use to implement position-specific training drills targeting key performance actions performed in games. For instance, game-based drills for guards should focus on improving assists with free-throw shooting also important. In turn, coaches should work on limiting turnovers and increasing defensive rebounding skills among forwards, while training drills optimizing 2-point shot accuracy, rebounding, and blocks appear key for centers.

Several significant effects were found for the current game contextual factors. In agreement with the effects observed for contextual factors in the previous game, a higher current game score differential was associated with more favourable statistics for both high- (points, 3P%, rebounds, steals, and turnovers) and medium-status (points, 2P%, 3P%, and assists) players. These results confirm that close games are more difficult, competitive, and characterised by poorer individual performances, while players may benefit from the lower physical, physiological (Fox et al., 2019a), and psychological constraints imposed by less balanced games. Regarding the game outcome, wins were associated with better performances of high-status players in key performance indicators (points and PIR), further confirming the importance of the players who receive the most playing time in a team. Differently, medium-status players' performances did not differ according to the game outcome, suggesting that this group of players may hold a less influential role in team success. Along these lines, current game location affected the performances of only low-status players, who collected more offensive rebounds and had more blocks at home compared to away games. The home advantage effects have been widely demonstrated in team sport research (Gómez-Ruano et al., 2021; Leota et al., 2022), where our findings add further insight into this aspect, suggesting that better players might be able to maintain consistent performances irrespective of the game location, which become more impactful in players receiving less playing time. A previous study (Sansone et al., 2024, 2023) suggested that teams have different performance profiles when competing in a European national league compared to the Euroleague. This study partly corroborates these previous findings where medium- and low-status players had poorer 1P% in the Euroleague playoffs than all phases of the domestic competition. Such games are particularly demanding and important, with increased psychological demands which seem to affect free-throw accuracy (Goldschmied et al., 2022); however, high-status players did not demonstrate such a reduction in 1P%, suggesting they may be able to better cope with associated pressures during important games when attempting free-throws (Goldschmied et al., 2022). Furthermore, the differences in fouls committed (higher in Euroleague playoffs for high-status players) and drawn (higher in Euroleague for high- and low-status players) suggest that there may be different levels of physicality and/or different refereeing styles across European basketball leagues that may underpin these trends. Our findings corroborate previous research (Goldschmied et al., 2022)and further suggest coaches should carefully consider contextual factors when planning game tactical strategies as they can explain up to 11% of the variance in players' performances.

This study has some limitations that need to be considered when interpreting the results and that should be addressed in further research. Firstly, given the findings for congested schedules on player performance contrasted results reported in some prior studies, future research should expand on our work to definitively clarify how game-related statistics may vary across different congested schedules in modern European basketball. Secondly, travel demands were shown to influences some game-related statistics but this effect varied by player status; thus, future studies should consider other relevant metrics which were not considered in this study, such as external and internal loads (Fox et al., 2019b; Gasperi et al., 2023), and athlete-reported outcome measures (Sansone et al., 2023). Additionally, we considered the end-of-season ranking to classify opponent level, which did not account for the variation in teams' performances across different timepoints within the season. Future research may extend on our work to explore how opponent level determined using current ladder position or form may impact players' performances. Furthermore, our findings might not be generalized to other populations (e.g., female or youth players) and male professional leagues (e.g., NBA) given the varied performance profiles observed and the potential for the investigated factors to exert different effects.

5. Conclusions

The findings from this study indicate that player performance varied significantly based on schedule congestion, travel demands, contextual factors, and player status. More precisely: (i) high-status players' performances were unaffected by game schedule but declined after games played against higher-level teams; (ii) medium-status players' defensive rebounds and fouls decreased with less time between games, while their offensive rebounds increased after final games; (iii) low-status players' defensive rebounds, turnovers, and 2P% were negatively impacted by greater travel distances between games; (iv) playing more minutes in previous games generally improved performance in the current across all player status clusters; (v) several positional differences were evident across all statuses, with guards excelling in free-throw accuracy and assists, forwards having fewer turnovers, and centers showing better 2P%, rebounds, and blocks; and (vi) home games benefitted only low-status players being associated with more offensive rebounds and blocks. Considering these varied results, it should be noted the R^2 values (0.02–0.24) and *small*-to-*medium* effect sizes found in the statistical models emphasize that individual player performances in elite European basketball leagues are only partially associated with the factors examined in this study. In turn, the complex, non-linear interactions among the factors examined as well as wider aspects like physical and physiological attributes (e.g., physical fitness attributes) as well as psychological properties likely play a combined role in players' performance in elite, European basketball competitions.

Disclosure statement

No potential conflict of interest was reported by the author(s).

ORCID

Pierpaolo Sansone http://orcid.org/0000-0002-7355-3795
Daniele Conte http://orcid.org/0000-0003-3551-1030

Lorenzo Gasperi http://orcid.org/0000-0001-6532-2180
Aaron T. Scanlan http://orcid.org/0000-0002-0750-8697
Miguel Angel Gomez-Ruano http://orcid.org/0000-0002-9585-3158

References

Calleja-González, J., Mallo, J., Cos, F., Sampaio, J., Jones, M. T., Marqués-Jiménez, D., Mielgo-Ayuso, J., Freitas, T. T., Alcaraz, P. E., Vilamitjana, J., Ibañez, S. J., Cuzzolin, F., Terrados, N., Bird, S. P., Zubillaga, A., Huyghe, T., Jukic, I., Lorenzo, A., Loturco, I., & Lago-Peñas, C. (2023). A commentary of factors related to player availability and its influence on performance in elite team sports. *Frontiers in Sports and Active Living*, *4*(January), 1–8. https://doi.org/10.3389/fspor.2022.1077934

Çene, E. (2018). What is the difference between a winning and a losing team: Insights from Euroleague basketball. *International Journal of Performance Analysis in Sport*, *18*(1), 55–68. https://doi.org/10.1080/24748668.2018.1446234

Conte, D., Kamarauskas, P., Ferioli, D., Scanlan, A. T., Kamandulis, S., Paulauskas, H., & Lukonaitienė, I. (2021). Workload and well-being across games played on consecutive days during in-season phase in basketball players. *The Journal of Sports Medicine and Physical Fitness*, *61*(4), 534–541. https://doi.org/10.23736/s0022-4707.20.11396-3

Cui, Y., Liu, F., Bao, D., Liu, H., Zhang, S., & Gómez, M.-Á. (2019). Key anthropometric and physical determinants for different playing positions during national basketball association draft combine test. *Frontiers in Psychology*, *10*, 2359. https://doi.org/10.3389/fpsyg.2019.02359

Delextrat, A., Badiella, A., Saavedra, V., Matthew, D., Schelling, X., & Torres-Ronda, L. (2015). Match activity demands of elite Spanish female basketball players by playing position. *International Journal of Performance Analysis in Sport*, *15*(2), 687–703. https://doi.org/10.1080/24748668.2015.11868824

Esteves, P. T., Mikolajec, K., Schelling, X., & Sampaio, J. (2021). Basketball performance is affected by the schedule congestion: NBA back-to-backs under the microscope. *European Journal of Sport Science*, *21*(1), 26–35. https://doi.org/10.1080/17461391.2020.1736179

Fox, J. L., Stanton, R., Sargent, C., & Power, C. J. (2019a). The Impact of contextual factors on game demands in starting, semiprofessional, male basketball players. *International Journal of Sports Physiology & Performance*, *10*, 1–7. https://doi.org/10.1123/ijspp.2019-0203

Fox, J. L., Stanton, R., Sargent, C., & Power, C. J. (2019b). The Impact of contextual factors on game demands in starting, semiprofessional, male basketball players. *International Journal of Sports Physiology & Performance*, *10*, 1–7. https://doi.org/10.1123/ijspp.2019-0203

Gasperi, L., Conte, D., Leicht, A., & Gómez-Ruano, M. Á. (2020). Game related statistics discriminate national and foreign players according to playing position and team ability in the women's basketball euroleague. *International Journal of Environmental Research and Public Health*, *17*(15), 1–10. https://doi.org/10.3390/ijerph17155507

Gasperi, L., Sansone, P., Gomez-Ruano, M. A., Lukonaitienė, I., & Conte, D. (2023). Female basketball game performance is influenced by menstrual cycle phase, age, perceived demands and game-related contextual factors. *Journal of Sports Sciences*, *00*(0), 1–8. https://doi.org/10.1080/02640414.2023.2285119

Goldschmied, N., Raphaeli, M., Moothart, S., & Furley, P. (2022). Free throw shooting performance under pressure: A social psychology critical review of research. *International Journal of Sport & Exercise Psychology*, *20*(5), 1397–1415. https://doi.org/10.1080/1612197X.2021.1979073

Gómez, M. Á., Avugos, S., Oñoro, M. Á., Lorenzo, A., & Bar-Eli, M. (2018). Shaq is not alone: Free-throws in the final moments of a basketball game. *Journal of Human Kinetics*, *62*(1), 135–144. https://doi.org/10.1515/hukin-2017-0165

Gómez, M. A., Lorenzo, A., Barakat, R., Ortega, E., & José, M. P. (2008). Differences in game-related statistics of basketball performance by game location for Men's winning and losing teams. *Perceptual and Motor Skills*, *106*(1), 43–50. https://doi.org/10.2466/pms.106.1.43-50

Gómez, M. Á., Lorenzo, A., Sampaio, J., & Ibáñez, S. J. (2006). Differences in game-related statistics between winning and losing teams in women's basketball. *Journal of Human Movement Studies*, *51*(5), 357–369.
Gómez, M. Á., Silva, R., Lorenzo, A., Kreivyte, R., & Sampaio, J. (2017). Exploring the effects of substituting basketball players in high-level teams. *Journal of Sports Sciences*, *35*(3), 247–254. https://doi.org/10.1080/02640414.2016.1161217
Gómez-Ruano, M., Pollard, R., & Lago-Peñas, C. (2021). *Home advantage in sport: Causes and the effect on performance* (1st ed.). Routledge.
Koyama, T., Nishikawa, J., Yaguchi, K., Irino, T., & Rikukawa, A. (2024). A comparison of the physical demands generated by playing different opponents in basketball friendly matches. *Biology of Sport*, *41*(1), 253–260. https://doi.org/10.5114/biolsport.2024.129474
Leicht, A. S., Gomez, M. A., & Woods, C. T. (2017). Team performance indicators explain outcome during women's basketball matches at the olympic games. *Sports*, *5*(4), 96. https://doi.org/10.3390/sports5040096
Leota, J., Hoffman, D., Mascaro, L., Czeisler, M. E., Nash, K., Drummond, S. P. A., Anderson, C., Rajaratnam, S. M. W., & Facer-Childs, E. R. (2022). Home is where the hustle is: The influence of crowds on effort and home advantage in the national basketball association. *Journal of Sports Sciences*, *40*(20), 2343–2352. https://doi.org/10.1080/02640414.2022.2154933
Lorenzo, J., Lorenzo, A., Conte, D., & Giménez, M. (2019). Long-Term analysis of elite basketball players ' game-related statistics throughout their careers. *Frontiers in Psychology*, *10*. https://doi.org/10.3389/fpsyg.2019.00421
Mateus, N., Esteves, P., Gonçalves, B., Torres, I., Gomez, M. A., Arede, J., & Leite, N. (2020). Clustering performance in the European basketball according to players' characteristics and contextual variables. *International Journal of Sports Science & Coaching*, *15*(3), 405–411. https://doi.org/10.1177/1747954120911308
Mateus, N., Gonçalves, B., Abade, E., Liu, H., Torres-Ronda, L., Leite, N., & Sampaio, J. (2015). Game-to-game variability of technical and physical performance in NBA players. *International Journal of Performance Analysis in Sport*, *15*(3), 764–776. https://doi.org/10.1080/24748668.2015.11868829
Sampaio, J., Ibanez, S. J., Gomez, M. A., Lorenzo, A., & Ortega, E. (2008). Game location influences basketball players' performance across playing positions. *International Journal of Sport Psychology*, *39*(3), 205–216.
Sansone, P., Ceravolo, A., & Tessitore, A. (2021). External, internal, perceived training loads and their relationships in youth basketball players across different positions. *International Journal of Sports Phyisiology and Performance*, *17*(2), 249–255. https://doi.org/10.1123/ijspp.2020-0962
Sansone, P., Gasperi, L., Conte, D., Scanlan, A. T., Sampaio, J., & Gómez-Ruano, M. Á. (2024). Game schedule, travel demands and contextual factors influence key game-related statistics among the top European male basketball teams. *Journal of Sports Sciences*, 1–8. https://doi.org/10.1080/02640414.2024.2409557
Sansone, P., Gasperi, L., Makivic, B., Gomez-Ruano, M. A., Tessitore, A., & Conte, D. (2023). An ecological investigation of average and peak external load intensities of basketball skills and game-based training drills. *Biology of Sport*, *40*(3), 649–656. https://doi.org/10.5114/biolsport.2023.119291
Sansone, P., Gasperi, L., Tessitore, A., & Gomez, M. A. (2021). Training load, recovery and game performance in semi-professional male basketball: Influence of individual characteristics and contextual factors. *Biology of Sport*, *38*(2), 207–217. https://doi.org/10.5114/BIOLSPORT.2020.98451
Sansone, P., Rago, V., Kellmann, M., & Alcaraz, P. E. (2023). Relationship between athlete-reported outcome measures and subsequent match performance in team sports: A systematic review. *The Journal of Strength & Conditioning Research*, *33*(11), 2302–2313. https://doi.org/10.1519/JSC.0000000000004605
Svilar, L., Castellano, J., Jukic, I., & Casamichana, D. (2018). Positional differences in elite basketball: Selecting appropriate training-load measures. *International Journal of Sports Physiology & Performance*, *13*(7), 947–952. https://doi.org/10.1123/ijspp.2017-0534

Wang, X., Zhang, S., Gasperi, L., Robertson, S., & Ruano, M. A. G. (2023). Rest or rust? Complex influence of schedule congestion on the home advantage in the national basketball association. *Chaos, Solitons & Fractals*, *174*(July), 113698. https://doi.org/10.1016/j.chaos.2023.113698

Yang, J., Wu, C., Zhou, C., Zhang, S., Leicht, A. S., & Gomez, M. Á. (2021). Influence of Match Congestion on Performances in the National Basketball Association. *Frontiers in Psychology*, *12* (February), 1–8. https://doi.org/10.3389/fpsyg.2021.630769

Zhang, S., Lorenzo, A., Gómez, M.-A., Mateus, N., Gonçalves, B., & Sampaio, J. (2018). Clustering performances in the NBA according to players' anthropometric attributes and playing experience. *Journal of Sports Sciences*, *36*(22), 2511–2520. https://doi.org/10.1080/02640414.2018.1466493