ORIGINAL SCIENTIFIC PAPER

Load Dynamics in Basketball: Insights from Wins and Losses

Igor Vučković[1], László Rátgéber[2], Dóra Nagy[2], Dimitrije Čabarkapa[3], Mladen Mikić[4], Filip Kukić[1]

Affiliations: [1]Faculty of Physical Education and Sport, University of Banja Luka, Banja Luka, RS, Bosnia and Herzegovina, [2]Faculty of Health Sciences, University of Pecs, Pecs, Hungary, [3]Jayhawk Athletic Performance Laboratory – Wu Tsai Human Performance Alliance, Department of Health, Sport and Exercise Science, University of Kansas, Lawrence, Kansas, USA, [4]Faculty of Sport and Physical Education, University of Novi Sad, Serbia

Correspondence: F. Kukić. University of Banja Luka, Faculty of Physical Education and Sports, Bulevar vojvode Petra Bojovića 1A, Banja Luka, Republika Srpska, Bosna i Herzegovina. Email: filip.kukic@ffvs.unibl.org

Abstract

The purpose of the present study was to: determine differences in external and internal load in professional male basketball players between winning and losing game outcomes during official in-season games; identify differences in external and internal loads between backcourt and frontcourt players in both winning and losing games; and examine if load variables impact the Performance Index Rating (PIR). Using the performance monitoring system (Kinexon), 20 player load metrics were analysed for eight athletes. Paired sample t-tests or their nonparametric equivalents, independent sample t-tests or their nonparametric equivalents, and stepwise regression analysis were used to examine statistically significant differences and determine the association of load variables with PIR. The results revealed no significant differences between the winning and losing game outcomes in external and internal load metrics on a general and partial level. However, significant differences were observed between backcourt and frontcourt players in both winning and losing matches. Training impulse, average heart rate, and Sprints explained 53% (adjusted R^2=0.53, p<0.001) of the variance in PIR of backcourt players, while Accumulated Acceleration Load and number of Accelerations explained 46% (adjusted R^2=0.462, p=0.02) of the variance in PIR of frontcourt players. While player loads did not directly impact game outcomes, they did affect players' PIR and varied by playing position. These insights are valuable for the head coach and the team's strength and conditioning personnel and could aid in the development of tailored training programs to enhance player performance and recovery.

Keywords: *backcourt players, frontcourt players, PIR, Kinexon, performance analysis*

@MJSSMontenegro
EXTERNAL AND INTERNAL LOAD DYNAMICS IN BASKETBALL
http://mjssm.me/?sekcija=article&artid=306

Cite this article: Vučković, I., Rátgéber, L., Nagy, D., Čabarkapa, D., Mikić, M., Kukić, F. (2026) Load Dynamics in Basketball: Insights from Wins and Losses. *Montenegrin Journal of Sports Science and Medicine, 22 (1)*, Ahead of print. https://doi.org/10.26773/mjssm.260301

Introduction

Monitoring training load is essential to maximize performance, prevent overreaching, and reduce injury risks (Aoki et al., 2017). Prioritizing the use of game-collected data is essential to accurately determine training loads, particularly for designing individually tailored training programs (Svilar et al., 2018). Obtaining the player load values for games is challenging due to various contextual factors influencing the game demands, such as game location (e.g., home or away) and game outcome (i.e., win or loss) (Fox et al., 2020). Previous research

Received: 29 April 2025 | Accepted after revision: 08 July 2025 | Early access publication date: 01 August 2025 | Final publication date: 15 March 2026

Conflict of interest: None declared.

on the external and internal load of basketball players has followed three main directions.

The first group of studies focused on the external and internal load of basketball players in various contexts (Fox et al., 2020; Sansone et al., 2021; Svilar et al., 2018). Fox et al. (2020) reported significant differences in player loads in away vs. home games, balanced vs. unbalanced, and wins vs. loses. Considering the influence of individual characteristics and contextual factors on game performance, Sansone et al. (2021) emphasized the significance of conditions where players experience high and low loads. High loads included being a guard, having high experience, medium minutes per game, during the early season, and their combinations, while low loads meant situations like low minutes per game or facing a high-level upcoming opponent.

The second group of scientific articles has examined the differences between backcourt (i.e., guards) players and frontcourt (i.e., forwards and centers) players in their external and internal load (Salazar et al., 2020; Vázquez-Guerrerol et al., 2018; Williams et al., 2021). Vázquez-Guerrero1 et al. (2018) emphasized the greater importance of deceleration over accelerations in basketball players, whereby frontcourt players exhibited higher acceleration-to-deceleration ratio of over 3 m/s2. Using the principal component analysis, Salazar et al. (2020) found that components of external load rank differently between playing positions, with accelerations and decelerations being the most dominant. Williams et al. (2021) found that frontcourt players experienced greater external and internal loads in games compared to training. Authors concluded that position specific strategies may be needed to optimize players performance. The third group of studies investigated the impact of various player performances on the Performance Index Rating (PIR) (Fox et al., 2022; Sansone et al., 2021; Zarić et al., 2018).

To the best of our knowledge, there is a lack of research addressing external and internal load of professional basketball players in official winning vs. losing matches. Therefore, the first aim of this study was to determine whether there are differences in the external and internal load of professional male basketball players in winning and losing matches. The second aim was to identify differences between backcourt players and frontcourt players in the external and internal load in winning and losing matches. The third aim was to investigate whether the variables of external and internal load influence the PIR of basketball players in winning and losing matches. Accordingly, we hypothesized that there would be no significant differences in any selected variables of external and internal load in winning and losing matches; that backcourt and frontcourt players would not differ in the external and internal load in winning and losing matches; and that there would be an impact of external and internal load on the PIR of basketball players in winning and losing matches.

Methods

A prospective observational research design was adopted to examine external and internal load of an elite male basketball team playing in the Hungarian First League Championship. Data were collected using the Kinexon System (KINEXON Precision Technologies, Munich, Germany) during eight home games (i.e., wins = 5, losses = 3) of the 2023/2024 season, from October to January. Kinexon is an ultra-wideband local positioning system (LPS) with sub-10 cm accuracy and 20 ms latency. It offers over 300 real-time metrics by pairing wearable sensors with Wi-Fi-connected anchors. Utilizing ultra-wideband signals, its small sensors track players' real-time positions with the frequency of 20Hz. The system precisely measures 2D and 3D movements, directional changes, and performance/load metrics for all players. Its validity and reliability were shown to be acceptable (Fleureau et al., 2020; Gamble et al., 2023). Players wore inertial measurement unit sensors in a manufacturer-designed vest, on their back, and a Suunto sensor to deliver data of heart rate changes. System was set to measure movements on the court not on the bench, while heart rate sensor data were collected both on the bench and on the court during the whole training session or game. The ethical approval was obtained by a Human Research Ethics Committee of the Faculty of Physical Education and Sports, University of Banja Luka (No. 11/505-2/23). The study is conducted following the Helsinki Declaration (Williams, 2008).

Subjects

Data from eight male professional basketball players (mean±SD, age = 24.5±4.8 years; height = 199.2±7.6 cm; body mass = 95.4±10.8 kg) in the Hungarian Basketball League 2023/2024 Championship were analysed. All athletes were cleared for participation in training and competition by their respective medical and strength and conditioning staff. None of the players participated in the observed games while sick or injured. Only athletes that played >8 min per game were included in the study analysis procedures. This was recommended by the head coach as players who played <8 min per game typically involved young players with specific roles or those in recovery, neither of whom significantly contributed to the team (2.44% of total playing time). Following Russell et al. (2020), players were classified as frontcourt players (n = 3; centers) and backcourt players (n = 5; forwards and guards).

Procedures

Kinexon is an ultra-wideband local positioning system (LPS) with sub-10 cm accuracy and 20 ms latency. It offers over 300 real-time metrics by pairing wearable sensors with Wi-Fi-connected anchors. Utilizing ultra-wideband signals, its small sensors track players' real-time positions with the frequency of 20Hz. The system precisely measures 2D and 3D movements, directional changes, and performance/load metrics for all players. Its validity and reliability were shown to be acceptable (Blauberger et al., 2021; Gamble et al., 2023). Players wore inertial measurement unit sensors in a manufacturer-designed vest, on their back, and a Suunto sensor to deliver data of heart rate changes. System was set to measure movements on the court not on the bench, while heart rate sensor data were collected both on the bench and on the court during the whole training session or game.

Variables

The following variables were analysed:

Distance Covered

Player's total distance covered during the game (Distance [m]) was calculated as the sum of minimum distances

DOI 10.26773/mjssm.260301

updated within a minimum time frame of 0.5 meters and 1.0 second intervals. The distance covered was relativized to time (Distance [m/min]) to provide an indication of player's locomotion intensity.

On-court Speed

The speed of a player was collected at each single instant of time based on the differentiation of filtered positions. Average running speed ($Speed_{Avg}$ [km/h]) and maximum running speed ($Speed_{Max}$ [km/h]) during the game were extracted for the analysis.

Number of Sprints

A sprint event was triggered when a player maintains a speed over a given speed threshold during a minimum duration. Speed threshold was 15.12 km/h and the minimum duration was 0.5 s. A total number of sprints (Sprint [No]) and relativized number of sprints per minute spent on the court (SprintsN [No/min]) were extracted for the analysis.

Acceleration and Deceleration events

Acceleration and deceleration events occurred when a player sustained acceleration above a threshold (1.5 m/s^2) for a minimum duration of 0.5 seconds. For this study, we extracted total counts of accelerations (Accelerations [No]) and decelerations (Decelerations [No]), as well as their respective rates per minute ($Accelerations_N$ [No/min] and $Decelerations_N$ [No/min]). The maximum deceleration of the player (Deceleration max [m/s^2]) was calculated by performing filtering and double differentiation of position data.

Accumulated Acceleration Load

This metric provides the accumulated load of the player during the entire game (Boyd et al., 2011). It adds up the differentials of accelerometer data in a single number, providing an overview of the load of the player produced by 2D-motion, jumps, impacts. The instantaneous acceleration load is based on the player load formula defined elsewhere (Boyd et al., 2011).

Number of Jumps

This variable assesses the total number of jumps (Jumps [No]) and relativized number of jumps (JumpsN [No/min]) during the player's in-game time. Each jump exceeding a minimum airtime is detected via accelerometer data, accurately pinpointing the start and end of the jump. Jump height can be computed from airtime using the formula: Height = (0.5g * airtime + (height difference between take-off and landing height / airtime))^2 / 2g. The minimum airtime was 0.3s.

Jump Load per Player's Body Mass

The energy estimation is based on the jump height for each individual jump. The jump load of a single jump is calculated using the potential energy formula: Jump Load (J/kg) = gravity constant * jump height. Jump Load (J) = mass of the player in kg * gravity constant * jump height. The jump load of every single jump performed by a player is added to yield an overall jump load for that player.

Heart rate

The heart rate data for each player is measured by Suunto sensors worn in the Kinexon vest. Average values (HRavg [b/min]) obtained during the game were assessed. In addition, heart rate relative to the personal maximal value (HRmax [%]) obtained on treadmill at the beginning of season was also calculated for each game. We updated the values if the measured maximum heart rate was higher for more than three times.

Training Impulse

We used Training Impulse (TRIMP) as an indicator of overall game load and metabolic functionality (Stagno et al., 2007). The TRIMP formula is the following: fractionalElevation = (HRi - HRmin) / (HRmax - HRmin) TRIMP = SUM (0.1225 * e3.9434 * fractionalElevation) * sessionTime where: "HRi" is the instantaneous (current) heart rate of the player (in bpm); "HRmin" is the minimum heart rate of the player (in bpm;) "HRmax" is the maximum heart rate of the player (in bpm); "sessionTime" is the duration of the training/game in minutes (Stagno et al., 2007).

Statistical analyses

Statistical procedures were performed using JASP statistical software (v 0.18.1, University of Amsterdam, Netherlands). The descriptive statistics were shown for mean, standard deviation, minimum, and maximum. The Shapiro-Wilk test was performed to test the normality of data distribution. For variables with violated normality of distribution, non-parametric tests were performed. The difference between games won and games lost was tested using the paired sample t-test (Wilcoxon signed-rank for non-parametric data). An independent sample t-test (Mann-Whitney test for non-parametric data) was used to test the differences between backcourt and frontcourt players. The regression analysis with stepwise model was utilized to determine the association of external and internal load variables with PIR. This model was selected to reduce the number of variables to those that best predict the PIR. The significance was set at $p<0.05$. The effect sizes were calculated for differences (Cohen's d) as $d < 0.2$ (trivial), d = 0.2-0.5 (small), d = 0.5-0.8 (moderate), 0.8-1.2 (large), and $d > 1.2$ (large) and for the coefficient of determination (r^2) as r^2 = 0.04-0.25 (small), r^2 = 0.25-0.64 (moderate), and $r^2 > 0.64$ (large) (Sullivan & Feinn, 2012). G*Power (v 3.1.9.4, Kiel University, Germany) was used to determine the required effect size for the given sample size.

Results

There was no significant difference between winning and losing game outcomes in indicators of external and internal load on a general level (p = 0.5–0.95, d = 0.02–0.37), as well as on a partial level. The descriptive statistics for won and lost games are presented in Tables 1 and 2, respectively. The normality of distribution was violated for PIR, Jumps, and HRmax in games lost; and for PIR, Jumps, JumpLoadPerMass, and HR in games lost. Thus, the non-parametric statistical tests were used for those variables. The effect size analysis also did not indicate difference of considerable size in these indicators (Cohen's d = 0.01–0.37). Considering the difference between the backcourt and frontcourt players in winning and losing matches, significant differences occurred in a number of variables (Table 1 and Table 2).

The stepwise regression analysis determined significant association of external and internal load indicators with the

Table 1. Descriptive statistics and between-position differences for games won.

Group Descriptives	Backcourt players		Frontcourt players		p	d	95% CI for d	
	Mean	SD	Mean	SD				
PIR	9	9.27	20.31	7.3	p < 0.001	-1.29	-1.97	-0.59
Distance (m)	3761	1346.33	5030.85	1083.47	p < 0.001	-0.99	-1.66	-0.31
DistanceN (m/min)	71.06	6.19	68.69	3.07	0.2	0.43	-0.22	1.07
$Speed_{Avg}$ (km/h)	4.27	0.38	4.12	0.18	0.18	0.45	-0.2	1.09
$Speed_{Max}$ (km/h)	24.22	1.95	23.77	0.94	0.43	0.26	-0.38	0.9
Sprints (No)	38.65	16.81	37.69	5.86	0.84	0.06	-0.57	0.7
$Sprints_{N}$ (No/min)	0.73	0.22	0.53	0.12	p < 0.001	1.02	0.34	1.69
Accelerations (No)	338.12	122.58	455	102.38	p < 0.001	-0.99	-1.66	-0.32
$Accelerations_{N}$ (No/min)	6.39	0.55	6.2	0.32	0.25	0.38	-0.26	1.03
Decelerations (No)	323.21	116.11	425.15	90.65	p < 0.001	-0.93	-1.59	-0.26
$Decelerations_{N}$ (No/min)	6.12	0.6	5.81	0.39	0.09	0.56	-0.09	1.21
$Deceleration_{max}$ (m/s2)	-3.82	0.49	-3.46	0.37	0.02	-0.76	-1.42	-0.1
AccumAccelLoad (J)	375.87	132.19	489.2	95.38	p < 0.001	-0.92	-1.58	-0.25
$AccumAccelLoad_{N}$ (/min)	7.12	0.55	6.7	0.33	0.01	0.83	0.17	1.49
Jumps (No)	38.62	22.43	77	22.3	p < 0.001	-1.71	-2.44	-0.98
$Jumps_{N}$ (No/min)	0.7	0.23	1.05	0.15	p < 0.001	-1.66	-2.37	-0.92
JumpLoadPerMass (J/kg)	2.33	0.78	3.37	0.46	p < 0.001	-1.47	-2.17	-0.75
HRavg (bpm)	134.56	15.25	142.46	7.47	0.08	-0.58	-1.23	0.07
HRmax (bpm)	187.38	17.62	185.46	3.43	0.7	0.13	-0.51	0.77
HR% (% of max.)	68.38	7.33	73.23	5.93	0.04	-0.69	-1.35	-0.04
TRIMP	117.52	61.71	168.82	52.41	0.01	-0.86	-1.52	-0.2

Table 2. Descriptive statistics and between-position differences for games lost.

Variables	Backcourt players		Frontcourt players		p	d	95% CI for d	
	Mean	SD	Mean	SD				
PIR	7.05	16.43	7.44	14.22	0.03	-0.99	-1.88	-0.07
Distance (m)	3423.9	1111.24	4593.14	1257.56	0.03	-1.02	-1.91	-0.1
$Distance_{N}$ (m/min)	72.05	9.11	66.57	4.58	0.14	0.66	-0.22	1.54
$Speed_{Avg}$ (km/h)	4.32	0.55	3.99	0.27	0.14	0.66	-0.22	1.54
$Speed_{Max}$ (km/h)	23.82	1.89	24.26	1.07	0.57	-0.25	-1.12	0.61
Sprints (No)	37.75	17.12	35.71	8.48	0.77	0.13	-0.73	0.99
$Sprints_{N}$ (No/min)	0.8	0.29	0.53	0.11	0.03	1.03	0.11	1.93
Accelerations (No)	304.35	103.3	420.29	112.84	0.02	-1.1	-2	-0.18
$Accelerations_{N}$ (No/min)	6.37	0.73	6.1	0.48	0.38	0.39	-0.48	1.25
Decelerations (No)	288.25	98.25	400.57	113.04	0.02	-1.1	-2	-0.18
$Decelerations_{N}$ (No/min)	6.04	0.8	5.77	0.42	0.4	0.37	-0.5	1.24
$Deceleration_{max}$ (m/s2)	-3.55	0.45	-3.52	0.48	0.87	-0.07	-0.93	0.79
AccumAccelLoad (J)	341.54	112.59	460.11	130.61	0.03	-1.01	-1.91	-0.1
$AccumAccelLoad_{N}$ (/min)	7.17	0.86	6.63	0.33	0.13	0.69	-0.2	1.57
Jumps (No)	35.3	15.34	66.86	25.32	p < 0.001	-1.73	-2.7	-0.73
$Jumps_{N}$ (No/min)	0.73	0.18	0.95	0.17	0.01	-1.19	-2.1	-0.26
JumpLoadPerMass (J/kg)	2.43	0.64	3.01	0.42	0.03	-0.98	-1.88	-0.07
HRavg (bpm)	134.25	12.49	138.86	18.23	0.46	-0.33	-1.19	0.54
HRmax (bpm)	188.2	13.11	172.43	29.89	0.06	0.85	-0.05	1.73
HR% (% of max.)	68	7.53	71.43	11.9	0.38	-0.39	-1.25	0.48
TRIMP	102.45	42.75	179.77	61.66	p < 0.001	-1.61	-2.57	-0.63

 DOI 10.26773/mjssm.260301

PIR (adjusted $R^2 = 0.58$, $F = 26.61$, $p = 0.01$). The best model of prediction included TRIMP, Jumps, HRavg, and Sprints. However, considering that backcourt and frontcourt players were different in most of the variables and produced different PIR, the regression analysis was performed for each group separately as well. In both groups, external and internal load indicators were significant predictors of PIR (Figure 1). The prediction coefficients and multicollinearity are shown in Table 3. The regression analysis for backcourt players showed that 53% of the variation in PIR is determined by TRIMP, HRavg, and Sprints (adjusted $R^2 = 0.53$, $F = 20.890$, $p < 0.001$). Somewhat lower association was found in in frontcourt players (adjusted $R^2 = 0.462$, $F = 9.148$. $p = 0.02$) with 46% of explained variance in PIR by AccumAccelLoad and Accelerations$_N$. The variance inflation factor was indicated acceptable multicollinearity.

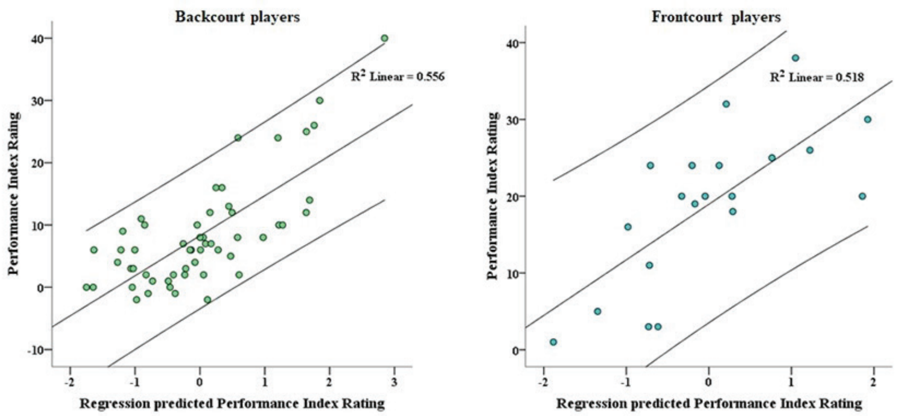

Figure 1. Scatterplot for backcourt and frontcourt players.

Table 3. Regression coefficients for perimeter and post players.

Model		Unstandardized coefficients		95% confidence interval		VIF
		B	Std. Error	Lower Bound	Upper Bound	
All players combined	(Constant)	-36.19***	9.76	-55.67	-16.72	
	TRIMP	0.05*	0.02	0.01	0.10	3.2
	Jumps	0.11*	0.05	0.01	0.20	2.6
	HRavg	0.31***	0.09	0.13	0.49	2.6
	Sprints	-0.17*	0.07	-0.32	-0.03	1.9
Perimeter players	(Constant)	-39.92	9.82	-59.65	-20.19	
	TRIMP	0.08***	0.02	0.04	0.12	1.8
	HRbpm	0.34***	0.09	0.16	0.52	2.4
	Sprints	-0.17*	0.07	-0.32	-0.02	2.4
Post players	(Constant)	53.95	29.20	-7.65	115.55	
	AccumAccelLoad	0.06**	0.02	0.02	0.09	1.0
	AccelerationsN	-10.10*	4.52	-19.64	-0.55	1.0

Note: *Significant at $p < 0.05$, **Significant at $p < 0.01$, ***Significant at $p < 0.001$. VIF - variance inflation factor.

Discussion

The purpose of the present study was to: a) determine differences in external and internal load in professional male basketball players between winning and losing game outcomes during official in-season games, b) identify differences in external and internal loads between backcourt and frontcourt players in both winning and losing games, and c) examine if external and internal load variables impact the PIR. Key findings suggest that player loads have no impact on game outcomes (i.e., wins vs. losses). However, significant differences were present in loads and PIR between player positions, supporting the initial two study's hypotheses. Furthermore, a significant association was found between player loads and performance (PIR), with load indicators varying across positions, confirming the third study hypothesis.

Given the absence of statistically significant distinctions across the 20 analysed indicators suggests that alternative determinants such as caliber of adversaries, psychological variables, and technical-tactical facets may have wielded a substantial impact on game outcomes. This is not unexpected, given the level of athletes examined in the present investigation (i.e., Hungarian First League). This suggests that players from the present study provided their best physical performance regardless of winning or losing and that this context did not play a role in players' commitment. In the investigation conducted by Ferioli et al. (2021), the internal workloads, as quantified through subjective session rating of perceived exertion (s-RPE), remained unchanged ($p > 0.05$) between playoff matches and regular season encounters. Notably, their cohort of athletes comprised professional basketball players from the First Italian League, suggesting a consistent level of effort across competitive phases due to their vocational commitment. Conversely, the findings by Koyama et al. (2024) revealed playing against stronger opponents produced higher external load, a trend not observed in our investigation. Intriguingly, the internal loads assessed via RPE were lower following matches against stronger teams compared to those against weaker ones. It is essential, however, to note that the participants in Koyama et al. (2024) study were collegiate-level players, potentially introducing variability due to their ongoing development and not yet reaching peak basketball performance.

Considering both backcourt and frontcourt players, it can be noted that the team analysed in this study exhibited certain specificities. Frontcourt players exhibited heightened involvement across a spectrum of performance metrics in both winning and losing scenarios. Despite occasional superior performance by guards, it is evident that frontcourt players carried a greater workload during gameplay. Frontcourt players covered a greater distance than backcourt players in both winning and losing matches, but there were no significant differences between them in distance covered per minute. Of note is that the distance covered by our sample was greater than that of the Spanish ACB league team analysed by Feu et al. (2023) but lower than in players analysed by Puente et al. (2017). This indicates that the basketball players in our study were on par with the top European teams in distance covered. In terms of speed measures, significant differences in SprintsN favour backcourt players in both winning and losing matches, which is not surprising considering the nature of their playing position (Stojanović et al., 2018).

The acceleration and deceleration data did not show consistent findings and preclude conclusions about activities related to accelerations and decelerations. This is in contrast with the findings of Vázquez-Guerrerol et al. (2018) and Salazar et al. (2020), who unequivocally state that backcourt players have higher player load in games. Conversely, frontcourt players performed better in all three jump variables in both winning and losing matches, which is consistent with their tasks in the game (Gamonales et al., 2023; Ibáñez et al., 2023). Compared to backcourt players, frontcourt players achieved higher values of HR% in winning games, as well as TRIMP in both winning and losing matches. TRIMP, as a measure of player exhaustion, further proves that frontcourt players of this team were more engaged than backcourt players. Modern basketball tactics impose numerous tasks on centers including sprinting in offense and defence, pick-and-roll play, and offensive and defensive rebounds. Within the highest levels of basketball, evidence suggests that the most efficient players tend to expend the least energy to achieve the most productive results (Caparrós et al., 2018; Sampaio et al., 2015). Thus, frontcourt-players seem to be more efficient in our team.

In the present investigation, it has been found that PIR correlated with both external and internal load indicators. When considering the entire team, TRIMP, Jumps, HRavg, and Sprints emerged as the most significant predictors of PIR. This information holds particular importance for team data analysts and head coaches. Given the distinct roles and physical demands placed on backcourt and frontcourt players, we conducted separate regression analyses, offering valuable insights for strength and conditioning coaches as well. TRIMP emerged as the most influential predictor of PIR for backcourt players. This suggests that the ability to tolerate or delay exhaustion played a crucial role in achieving higher PIR among backcourt players. Additionally, HRavg and the number of sprints during the game were identified as significant predictors. These parameters collectively reflect repeated sprint ability (Girard et al., 2011; Rodríguez-Fernández et al., 2019), indicating that superior cardiac function and the capacity for repetitive sprinting contributed to higher PIR. For frontcourt players, Accumulated Acceleration Load, representing metabolic work, emerged as a crucial factor influencing PIR. Notably, the frequency of accelerations was the second-best predictor of PIR. This underscores the importance of both the frequency of accelerations and the ability to either recover quickly or withstand performance fatigue (Edwards et al., 2018; Enoka & Duchateau, 2016) while executing on-court tasks for frontcourt players' PIR.

In summary, this study investigated external and internal load variations in basketball games between winning and losing game outcomes, as well as differences among backcourt and frontcourt players, aiming to establish associations with overall basketball performance. The findings suggest that while player loads do not directly impact game outcomes, they do correlate with player's PIR and vary across player positions. Our analysis identified TRIMP, Jumps, HRavg, and Sprints as significant predictors of PIR for the entire team. Separate regression analyses for backcourt and frontcourt players revealed distinct factors influencing PIR. For backcourt players, TRIMP, HRavg, and sprint frequency were crucial, emphasizing the importance of endurance and repeated sprint ability. On the other hand, Accumulated Acceleration Load and acceleration frequency emerged as key factors influencing PIR for frontcourt players, highlighting the importance of metabolic work and the ability to withstand performance fatigue. These insights are valuable for team management staff, and strength and conditioning practitioners, and can aid in the development of tailored training programs to enhance player performance and recovery. The statistical approach in the present study also offers a framework to navigate among the large number of variables that come from the player monitoring system.

Lastly, a limitation inherent in this study pertains to its reliance on a singular team for analysis, thereby restricting the generalizability of the findings and subsequent implications to other teams. However, it does provide the methodology on how to analyse a single team. It is advisable for future investigations to engage in concurrent longitudinal surveillance of multiple teams during matches, facilitating comparative analyses. The integration of internal-external load monitoring with PIR emerges as a promising methodology for assessing player quality, potentially representing an optimal or advantageous approach. Further research is warranted to determine if the findings of the present study are sex-specific (male vs. female) as well as if they remain applicable to other levels of basketball competition (e.g., collegiate).

Conclusions and practical application

The findings of this study offer several practical applications for basketball coaches, strength and conditioning practitioners, and sports scientists. Firstly, basketball coaches could use the proposed methodology to detect the main indicators of PIR in their team and individual players. This would help them design tailored training programs based on position-specific insights. Secondly, load management strategies could be optimized by monitoring key load indicators that emerged as game-important. For instance, in this study, to optimize game

 DOI 10.26773/mjssm.260301

performance TRIMP, HRavg, sprint frequency for backcourt players, and Accumulated Acceleration Load, acceleration frequency for frontcourt players were of importance. In teams with different player characteristics different indicators could be of importance, which could be accounted for using the methodology from the present study. Thirdly, coaches could develop game plans and tactics that leverage the strengths of each player position, informed by their game workload and performance characteristics.

Conflict of Interest

The authors declare that the research was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Acknowledgments

The authors would like to thank all the players and coaches of the Rátgéber Academy men's basketball team for participating in the study.

References

Aoki, M. S., Ronda, L. T., Marcelino, P. R., Drago, G., Carling, C., Bradley, P. S., & Moreira, A. (2017). Monitoring Training Loads in Professional Basketball Players Engaged in a Periodized Training Program. *The Journal of Strength & Conditioning Research*, *31*(2), 348. https://doi.org/10.1519/JSC.0000000000001507

Blauberger, P., Marzilger, R., & Lames, M. (2021). Validation of Player and Ball Tracking with a Local Positioning System. *Sensors*, *21*(4), Article 4. https://doi.org/10.3390/s21041465

Boyd, L. J., Ball, K., & Aughey, R. J. (2011). The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *International Journal of Sports Physiology and Performance*, *6*(3), 311–321. https://doi.org/10.1123/ijspp.6.3.311

Cabarkapa, D., Philipp, N. M., Cabarkapa, D. V., & Fry, A. C. (2023). Position-specific differences in countermovement vertical jump force-time metrics in professional male basketball players. *Frontiers in Sports and Active Living*, *5*, 1218234. https://doi.org/10.3389/fspor.2023.1218234

Cabarkapa, D. V., Cabarkapa, D., Eserhaut, D. A., & Fry, A. C. (2023). Relationship between internal and external load metrics in professional male basketball players. *Journal of Human Sport and Exercise*, *18*(4), Article 4. https://doi.org/10.14198/jhse.2023.184.01

Caparrós, T., Casals, M., Solana, Á., & Peña, J. (2018). Low External Workloads Are Related to Higher Injury Risk in Professional Male Basketball Games. *Journal of Sports Science & Medicine*, *17*(2), 289–297.

Edwards, T., Spiteri, T., Piggott, B., Bonhotal, J., Haff, G. G., & Joyce, C. (2018). Monitoring and Managing Fatigue in Basketball. *Sports*, *6*(1), Article 1. https://doi.org/10.3390/sports6010019

Enoka, R. M., & Duchateau, J. (2016). Translating Fatigue to Human Performance. *Medicine and Science in Sports and Exercise*, *48*(11), 2228–2238. https://doi.org/10.1249/MSS.0000000000000929

Ferioli, D., Scanlan, A. T., Conte, D., Tibiletti, E., & Rampinini, E. (2021). The Business End of the Season: A Comparison Between Playoff and Regular-Season Workloads in Professional Basketball Players. *International Journal of Sports Physiology and Performance*, *16*(5), 655–662. https://doi.org/10.1123/ijspp.2020-0405

Feu, S., García-Ceberino, J. M., López-Sierra, P., & Ibáñez, S. J. (2023). Training to Compete: Are Basketball Training Loads Similar to Competition Achieved? *Applied Sciences*, *13*(22), Article 22. https://doi.org/10.3390/app132212512

Fleureau, A., Lacome, M., Buchheit, M., Couturier, A., & Rabita, G. (2020). Validity of an ultra-wideband local positioning system to assess specific movements in handball. *Biology of Sport*, *37*(4), 351–357. https://doi.org/10.5114/biolsport.2020.96850

Fox, J. L., Stanton, R., O'Grady, C. J., Teramoto, M., Sargent, C., & Scanlan, A. T. (2022). Are acute player workloads associated with in-game performance in basketball? *Biology of Sport*, *39*(1), 95–100. https://doi.org/10.5114/biolsport.2021.102805

Fox, J. L., Stanton, R., Sargent, C., O'Grady, C. J., & Scanlan, A. T. (2020). *The Impact of Contextual Factors on Game Demands in Starting, Semiprofessional, Male Basketball Players*.

Gamble, A. S. D., Bigg, J. L., Pignanelli, C., Nyman, D. L. E., Burr, J. F., & Spriet, L. L. (2023). Reliability and validity of an indoor local positioning system for measuring external load in ice hockey players. *European Journal of Sport Science*, *23*(3), 311–318. https://doi.org/10.1080/17461391.2022.2032371

Gamonales, J. M., Hernández-Beltrán, V., Escudero-Tena, A., & Ibáñez, S. J. (2023). Analysis of the External and Internal Load in Professional Basketball Players. *Sports*, *11*(10), Article 10. https://doi.org/10.3390/sports11100195

Girard, O., Mendez-Villanueva, A., & Bishop, D. (2011). Repeated-sprint ability - part I: Factors contributing to fatigue. *Sports Medicine (Auckland, N.Z.)*, *41*(8), 673–694. https://doi.org/10.2165/11590550-000000000-00000

Ibáñez, S. J., Piñar, M. I., García, D., & Mancha-Triguero, D. (2023). Physical Fitness as a Predictor of Performance during Competition in Professional Women's Basketball Players. *International Journal of Environmental Research and Public Health*, *20*(2), 988. https://doi.org/10.3390/ijerph20020988

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

Puente, C., Abián-Vicén, J., Areces, F., López, R., & Del Coso, J. (2017). Physical and Physiological Demands of Experienced Male Basketball Players During a Competitive Game. *Journal of Strength and Conditioning Research*, *31*(4), 956–962. https://doi.org/10.1519/JSC.0000000000001577

Rodríguez-Fernández, A., Sanchez-Sanchez, J., Ramirez-Campillo, R., Nakamura, F. Y., Rodríguez-Marroyo, J. A., & Villa-Vicente, J. G. (2019). Relationship Between Repeated Sprint Ability, Aerobic Capacity, Intermittent Endurance, and Heart Rate Recovery in Youth Soccer Players. *The Journal of Strength & Conditioning Research*, *33*(12), 3406–3413. https://doi.org/10.1519/JSC.0000000000002193

Salazar, H., Castellano, J., & Svilar, L. (2020). Differences in External Load Variables Between Playing Positions in Elite Basketball Match-Play. *Journal of Human Kinetics*, *75*, 257–266. https://doi.org/10.2478/hukin-2020-0054

Sampaio, J., McGarry, T., Calleja-González, J., Jiménez Sáiz, S., Schelling I Del Alcázar, X., & Balciunas, M. (2015). Exploring Game Performance in the National Basketball Association Using Player Tracking Data. *PloS One*, *10*(7), e0132894. https://doi.org/10.1371/journal.pone.0132894

Sansone, P., Gasperi, L., Tessitore, A., & Gomez, M. (2021). Training load, recovery and game performance in semiprofessional male basketball: Influence of individual characteristics and contextual factors. *Biology of Sport*, *38*(2), 207–217. https://doi.org/10.5114/biolsport.2020.98451

Stagno, K. M., Thatcher, R., & van Someren, K. A. (2007). A modified TRIMP to quantify the in-season training load of team sport players. *Journal of Sports Sciences*, *25*(6), 629–634. https://doi.org/10.1080/02640410600811817

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. https://doi.org/10.1007/s40279-017-0794-z

Sullivan, G. M., & Feinn, R. (2012). Using effect size—Or why the *P* value is not enough. *Journal of Graduate Medical Education*, *4*(3), 279–282. https://doi.org/10.4300/JGME-D-12-00156.1

Svilar, L., Castellano, J., Jukic, I., & Casamichana, D. (2018). Positional Differences in Elite Basketball: Selecting Appropriate Training-Load Measures. *International Journal of Sports Physiology and Performance*, *13*(7), 947–952. https://doi.org/10.1123/ijspp.2017-0534

Vázquez-Guerrero, J., Suarez-Arrones, L., Casamichana Gómez, D., & Rodas, G. (2018). Comparing external total load, acceleration and deceleration outputs in elite basketball players across positions during match play. *Kinesiology*, *50.*(2.), 228–234. https://doi.org/10.26582/k.50.2.11

Williams, J. R. (2008). The declaration of Helsinki and public health. *Bulletin of the World Health Organization*, *86*(8), 650–652. https://doi.org/10.2471/BLT.08.050955

Williams, M. N. C., Dalbo, V. J., Fox, J. L., O'Grady, C. J., & Scanlan, A. T. (2021). Comparing Weekly Training and Game Demands According to Playing Position in a Semiprofessional Basketball Team. *International Journal of Sports Physiology and Performance*, *16*(6), 772–778. https://doi.org/10.1123/ijspp.2020-0457

Zarić, I., Dopsaj, M., & Marković, M. (2018). Match performance in young female basketball players: Relationship with laboratory and field tests. *International Journal of Performance Analysis in Sport*, *18*(1), 90–103. https://doi.org/10.1080/24748668.2018.1452109

DOI 10.26773/mjssm.260301