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Research article

Low External Workloads Are Related to Higher Injury Risk in Professional Male Basketball Games

Toni Caparrós [1,2]✉, Martí Casals [2], Álvaro Solana and Javier Peña [2,3]
[1] Institut Nacional d'Educació Física de Catalunya (INEFC), Barcelona, Spain; [2] Sport Performance Analysis Research Group (SPARG), Universitat de Vic, Vic, Spain; [3] UVic-UCC Sport and Physical Activity Studies Centre (CEEAF), Universitat de Vic, Vic, Spain

Abstract
The primary purpose of this study was to identify potential risk factors for sports injuries in professional basketball. An observational retrospective cohort study involving a male professional basketball team, using game tracking data was conducted during three consecutive seasons. Thirty-three professional basketball players took part in this study. A total of 29 time-loss injuries were recorded during regular season games, accounting for 244 total missed games with a mean of 16.26 ± 15.21 per player and season. The tracking data included the following variables: minutes played, physiological load, physiological intensity, mechanical load, mechanical intensity, distance covered, walking maximal speed, maximal speed, sprinting maximal speed, maximal speed, average offensive speed, average defensive speed, level one acceleration, level two acceleration, level three acceleration, level four acceleration, level one deceleration, level two deceleration, level three deceleration, level four deceleration, player efficiency rating and usage percentage. The influence of demographic characteristics, tracking data and performance factors on the risk of injury was investigated using multivariate analysis with their incidence rate ratios (IRRs). Athletes with less or equal than 3 decelerations per game (IRR, 4.36; 95% CI, 1.78-10.6) and those running less or equal than 1.3 miles per game (lower workload) (IRR, 6.42 ; 95% CI, 2.52-16.3) had a higher risk of injury during games ($p < 0.01$ in both cases). Therefore, unloaded players have a higher risk of injury. Adequate management of training loads might be a relevant factor to reduce the likelihood of injury according to individual profiles.

Key words: Game tracking, multivariate analysis, decelerations, distance, injury prevention.

Introduction

Injuries are a significant issue in professional sports such as basketball (Deitch, 2006). A detrimental effect in performance (Busfield et al., 2009) and a significant number of games missed due to injury at the end of the season have been highlighted in several studies on different professional male basketball leagues (Caparros et al., 2016; Podlog et al., 2015). Moreover, a significant inverse association between games missed due to injury and the percentage of won games at the end of the competitive season has also been confirmed in the past in professional male basketball (Podlog et al., 2015). Patellofemoral inflammation is the most significant injury regarding lost competition days, while ankle sprain is the most common injury among professional male basketball players (Drakos et al., 2010). The monetary impact that these sports injuries have on professional teams and franchises is not negligible. In the NBA, during the 2000-2015 period, losses between 10 and 50 million dollars per team and season due to injuries were reported (Talukder et al., 2016). Nevertheless, despite apparent interest and enormous research and practical efforts to prevent injuries, there is still no practical solution to decrease the injury incidence significantly in this family of sports.

To address this issue, a relationship between competitive schedule congestion and the occurrence of sports injuries has been studied previously (Drew and Finch, 2016; Teramoto et al., 2016). Increased incidence of sports injuries in specific periods within a season has been reported in some sports (Carling et al., 2016; Folgado et al., 2015). Level of competition and gender also seem to play a significant role in the epidemiological incidence (Anderson et al., 2003; Deitch, 2006; Gabbett and Domrow, 2007). High-level athletes are more prone to injuries due to competing demands. Thus, NBA players chances to suffer a game-related injury are twofold when compared to their collegiate counterparts (Deitch, 2006). Nevertheless, an increase in the number of sports injuries is observed at a sub-elite level too (Gabbett and Domrow, 2007).

A substantial number of initiatives have been presented to study the incidence of injuries in team sports (Drew and Finch, 2016; Ullah et al., 2012). Novel approaches to prevent and manage sports injuries tend to use technology consistently during competition. Player tracking (Sampaio et al., 2015), accelerometry (Colby et al., 2014) and global positioning systems (GPS) (Casamichana et al., 2013; Dellaserra et al., 2014; Rossi et al., 2017) are today's sports standard tools. Although the use of these technologies can be useful in all disciplines, they have spread mainly in team sports such as basketball (Caparrós et al., 2016; Sampaio et al., 2015), soccer (Casamichana et al., 2013; Osgnach et al., 2010), Australian football (Carey et al., 2016; Colby et al., 2014) and rugby (Gabbett and Domrow, 2007; Gabbett and Jenkins, 2011). In this processes, professional teams and researchers take advantage of technological innovations by using data obtained in stadiums and competition venues (Mangine et al., 2014; Sampaio et al., 2015). For instance, top football teams seem to rely on external training load variables such as acceleration, total distance, distance covered above specific speeds and metabolic power to make their decisions when managing training and competition loads (Nassis and Gabbet, 2017). The advantage is that average and peak speeds, accelerations or decelerations values (Casamichana et al.,

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2013), total distance traveled or the total number of high-intensity efforts performed while in training or competition (Carling et al., 2010) can be determined by the use of different electronic devices and systems, fairly frequent in elite sport. That is the case of player tracking, a technology that provides kinematic variables, while also enables a better understanding of physiological, technical and tactical variables (Mangine et al., 2014; Sampaio et al., 2015).

This data is essential in the field of injury prevention because different values of external and internal training loads can be employed to establish ratios that may indicate that the athlete is has been situated in a risk area (Gabbett, 2016). A vast body of literature has previously used external loads to find a consistent association between ratio values and the risk of injury (Colby et al., 2014; Drew and Finch, 2016; Gabbett and Jenkins, 2011; McNamara et al., 2017). The use of the acute:chronic workload ratio (ACWR) has allowed a better understanding of the relationship of workload and risk of injury (Gabbett and Jenkins, 2011; Hulin et al., 2013; 2016; Murray et al., 2017) in sports such as cricket (McNamara et al., 2017), football (Bowen et al., 2017) and rugby (Gabbett and Jenkins, 2011; Hulin et al., 2016). However, to our knowledge, only one study using this methodology has been conducted in professional basketball (Weiss et al., 2017). While providing an interesting starting point for workload-injury research in this sport, it was limited to one playing season. Given the popularity of this discipline, it seems of interest to establish whether a relationship exists between player workloads and injury risk in professional basketball by using data from more than one competitive season to reinforce the strength of statistical models.

The primary purpose of this study was to identify possible risk factors for injury related to variables from game tracking data in professional basketball to improve specific preventive strategies.

Methods

An observational, retrospective cohort study was conducted between October and April during three consecutive regular seasons, obtaining data from a total of 2613 observations and 246 games from 33 different players of a professional male basketball team. The use of these data attended to the standards of the Declaration of Helsinki, revised in Fortaleza (World Medical Association, 2013). Players were assigned an individual identifier code with the identity concealed, ensuring player anonymity was maintained.

Data collection was based on the methodology of the UEFA consensus statement for epidemiological studies (Hägglund et al., 2005). A time-loss injury was defined as any injury (contact and non-contact) occurring during a practice session or game which caused an absence for at least the next practice session or competition. Time-loss from associated injuries was retrospectively determined by the number of days of absence from participation.

All study data were available to the general public in open-access websites and included the demographic characteristics of the players, player tracking, injury and performance values. Tracking data were obtained from the website of the company STATS (http://stats.com/), responsible of the game tracking process in the competition (SportsVU, Northbrook, IL, USA) following the trend of previous studies (Embiricos and Poon, 2014; Hu et al., 2011; Lofti et al., 2011; Maymin, 2013; Siegle et al., 2013; Tamir and Oz, 2006). Injury information was obtained from public resources (www.rotoworld.com, www.cbs.com and http://www.basketball-reference.com/), following the same procedure with the performance data (http://stats.com/ and http://www.basketball-reference.com/). Again, several studies in the past have used this information showing its reliability (Gesbert et al., 2016; Maheswaran et al., 2012; Yonggangniu and Zhao, 2014). These records contained both non-tracking and tracking data. The different databases were then collated to assign the specific information about each game to each specific player. All 23 tracking and non-tracking variables presented by the companies designing the software were selected. Tracking variables were categorized into four main groups: physiological variables, speed and distance variables, mechanical load variables, and motor variables (Table 1).

Time-loss injuries suffered during regular season games were included in the study. There are no other exclusion criteria. Minutes and games played by every player were considered on the unbalanced study design with repeated measures. Given that not all of the players were observed for the same number of seasons, and that the number of games per season varied from one player to another. The possible risk variables for injuries considered were height, mass, age, season year, season month, won/lost game and home/away venue, minutes played, and the additional variables shown in Table 1.

Statistical analysis

A descriptive analysis of all variables of interest was carried out. In the case of categorical variables, absolute and relative frequencies were presented. For quantitative variables, measures of central tendency (mean and median) and statistical dispersion (standard deviation, percentiles 25th (P25), percentiles 75th (P75), and range) were calculated. To study the risk factors from the games tracking data variables, a generalized linear mixed model (GLMM) was conducted assuming the frequency of the injuries followed a Poisson's distribution. The same statistical approaches have been previously applied (Casals et al. 2015). Following the studies of Bolker (2009), Vanderbogaerde (2010) and Casals (2014), a list of relevant information and basic characteristics of the GLMM model were reported. The model expression for player i in his jth games is the following: $\log(\lambda_{ij}) = \log(m_{ij}) + X_{ij}\,\beta + u_i$ where $Y_{ij} \sim Po(\lambda_{ij})$. λ_{ij} is the number of injuries, m_{ij} is the number of minutes exposures of player, which is the offset of this model, and X_{ij} includes all independent variables of interest. The vector β contains the fixed effects, whereas u_i is the random effect corresponding to player i. The random effects are assumed to be independent and normally distributed: $u_i \sim N(0;\sigma^2)$, where σ_u^2 is the variance of random effect. The model accounted for repeated measures and the fact that the values of X_{ij} could change from one game to the next.

The simplification of the model was performed by backward selection of variables from the full model, and models were compared using the likelihood ratio test (LRT) until a minimal adequate model was obtained. Model selection was based on the Akaike Information Criterion (AIC). To estimate the model variables we used the Gauss-Hermite quadrature (GHQ) with 5 points (Bolker, 2009). The statistical significance of the fixed effects associated with the covariates included in the model was assessed using the Wald test. The correlation and the main possible interactions among the covariates were checked in the final model. A possible over-dispersion in the model was studied using Pearson's dispersion parameter (Bolker, 2009). Measures of association were calculated using incidence rate ratios (IRR) with 95% confidence intervals (CI). To prevent overfitting, a cross-validation procedure was completed using leave-one-out cross-validation (LOOCV). In the LOOCV, the prediction model is trained on data from all of the participants except one, which is "held out" and used as the test dataset. The process is repeated until all participants have served as the test data set. Moreover, the performances of estimation models were evaluated by the commonly used measures of goodness-of-fit: RMSE (Root Mean Square Error) and MAE (Mean Absolute Error). Finally, to assess the predictive or discriminatory ability of the model we performed the area under the curve (AUC) (Lopez-Raton et al., 2014).

Statistical significance was set at $p < 0.05$. To improve the interpretability of the clinical finding, suggestions made by Cook (2016) were followed, and continuous data were divided into categories (a dichotomized variable based on the approach of CatPredi library in R (Barrio et al., 2015). Also, facilitation of data interpretation was achieved by providing the IRR.

Table 1. Description of selected tracking and non-tracking (performance) factors.

TRACKING FACTORS (http://stats.com/)	
Acronym or name	**Description**
Physiological variables	
Physiological Load (Phy_Load)	Every 0.25 second throughout the course of a game the product of a player's mass, velocity and distance. Phy_Load = mass*average velocity*distance
Physiological Intensity (Phy_Int)	Physiological load, divided by every minute he plays. Phy_Int = Phy_Load /minutes played
Speed and distance variables	
Defensive average speed (Def_Average_Speed)	Average Speed Run on Defense (ml/h)
Offensive average speed (Off_Average_Speed)	Average Speed Run on Offense (ml/h)
Distance	Total distance run (ml)
Mechanical Load variables	
Mechanical Load (Mech_Load)	Measures the change of speed by a player throughout the course of the game. These are identified as accelerations and decelerations, derived from the changing of speeds throughout the locomotor activities (walk, jog, run, sprint, max). Each level includes a weighting factor to account for the severity of the acceleration and deceleration
Mechanical Intensity (Mech_Int)	Mechanical Load/minutes played
Acceleration (acc)	Increase in intensity that is maintained for at least one second
Level one acceleration (Acc_1)	0.5 m/s^2 acceleration
Level two acceleration (Acc_2)	1 m/s^2 acceleration
Level three acceleration (Acc_3)	2 m/s^2 acceleration
Level four acceleration (Acc_4)	4 m/s^2 acceleration
Deceleration (Dec)	Decrease in intensity level that is maintained for at least one second
Level one deceleration (Dec_1)	0.5 m/s^2 deceleration
Level two deceleration (Dec_2)	1 m/s^2 deceleration
Level three deceleration (Dec_3)	2 m/s^2 deceleration
Level four deceleration (Dec_4)	4 m/s^2 deceleration
Locomotor variables	
Walk maximal speed (WALK_MAX)	player individually achieved 0-20% of maximal speed
Run maximal speed (RUN_MAX)	player individually achieved 40-60% of maximal speed
Sprint maximal speed (SPRINT_MAX)	player individually achieved 60-80% of maximal speed
Maximal speed (MAX_MAX)	player individually achieved >80% of maximal speed
NON-TRACKING FACTORS (www.basketball-reference.com)	
Acronym or name	**Description**
Performance variables	
Player efficiency rating (PER)	Rating of a player's per-minute productivity (1 / MP) *[3P + (2/3) * AST + (2 - factor * (team_AST / team_FG)) * FG + (FT *0.5 * (1 + (1 - (team_AST / team_FG)) + (2/3) * (team_AST / team_FG)))- VOP * TOV- VOP * DRB% * (FGA - FG)- VOP * 0.44 * (0.44 + (0.56 * DRB%)) * (FTA - FT)+ VOP * (1 - DRB%) * (TRB - ORB)+ VOP * DRB% * ORB + VOP * STL + VOP * DRB% * BLK - PF * ((lg_FT / lg_PF) - 0.44 * (lg_FTA / lg_PF) * VOP)]
Usage percentage (Usg%)	An estimate of the percentage of team plays used by a player while he was on the floor: 100 * ((FGA + 0.44 * FTA + TOV) * (Tm MP / 5)) / (MP * (Tm FGA + 0.44 * Tm FTA + Tm TOV))

tm: team; lg: league; min: minutes played; AST: number of assists; 3P: number of three-point field goals made; FG: number of field goals made; FGA: number of field goals attempted; FT number of free throws made; FTA: number of free throws attempted; VOP: value of possession in reference to the league; TOV: number of turnovers; RB: number of rebounds; ORB: number of offensive rebounds; DRB: number of defensive rebounds; TRB: number of total rebounds; RBP, percentage of offensive or defensive; 1g: team pace value; MP: minute played

All statistical analyses were performed with the statistical package R (The R Foundation for Statistical Computing, Vienna, Austria), version 3.3.3. In particular, the R package lme4 (Bates, 2014) was used to fit the GLMM.

Results

The demographic characteristics of the 33 professional basketball players included in this study were: mean ± SD age of 24.9 ± 2.9 years, a height of 1.95 ± 0.09 m and a weight of 98.9 ± 12 kg. The team played 82 games every regular season, with a total exposure of 58457 minutes during all 7-month seasons (3 consecutive seasons). The team played an average of 3.4 games weekly during the competition. Data on tracking and non-tracking (performance) factors are shown in Table 2.

A total of 29 time-loss injuries were recorded throughout the study, involving 11 players, and accounting for 244 total missed games (MG) with a mean ± SD of 16.26 ± 15.21 per player and season. Of these, nine were in season 1, five were in season 2, and 15 were in the third season (Table 3).

Table 2. List and descriptive statistics of physiological and mechanical load, speed and distance, locomotor and performance variables.

Variables	Mean	SD	Minimum	P25	Median	P75	Maximum
Minutes	22.6	10.6	0.1	14.7	22.9	31.9	48.6
Phy_Load	740.6	354.3	0.9	479.4	739.2	1025.2	1613.4
Phy_Int	32.8	4.2	2.4	30.5	33	35.6	55.4
Mech_load	811.4	364.7	1.5	547	833.5	1113	1698.5
Mech_Int	36.7	4.5	3.9	33.9	36	38.8	64.9
Distance	1.6	0.7	0	1.1	1.6	2.2	3.4
Walk_Max	3.6	0.2	2.5	3.6	3.6	3.7	4.1
Run_Max	10.9	0.6	7.6	10.7	10.9	11.2	12.3
Sprint_Max	14.5	0.8	10.1	14.3	14.6	15	16.3
Max_Max	18.1	1.0	12.7	17.9	18.2	18.7	20.4
Off.Average Speed	4.5	0.4	0	4.3	4.5	4.7	12.9
Def.Average_Speed	3.9	0.5	0	3.7	3.9	4.1	16.7
Acc_1	233.4	111.5	0	152.0	233.0	324.5	561.0
Acc_2	79.4	39.1	0	50.0	79.0	110.0	194.0
Acc_3	14.5	7.7	0	9.0	14.0	20.0	54.0
Acc_4	0.7	1.0	0	0	0	1.0	6.0
Dec_1	153.0	72.8	1.0	99.0	153.0	210.0	364.0
Dec_2	103.6	46.7	0	70.0	107.0	141.0	223.0
Dec_3	6.5	4.1	0	4.0	6.0	9.0	29.0
Dec_4	0.3	0.6	0	0	0	0	4.0
PER	14.8	11.8	-41.4	7.7	14.7	21.6	210.8
Usg%	18	8.1	0	12.7	17.9	22.8	116.4

Minutes: minutes played; Phy_Load: physiological load; Phy_Int: physiological intensity; Mech_Load: mechanical load; Mech_Int: mechanical intensity; Distance: distance; WALK_MAX: walk maximal speed; RUN_MAX: run maximal speed; SPRINT_MAX: sprint maximal speed; MAX_MAX: maximal speed; Off_Average_speed: offensive average speed; Def_Average_Speed: defensive average speed; Accel_1: level one acceleration; Accel_2: level two acceleration; Accel_3: level three acceleration; Accel_4: level four acceleration; Decel_1: level one deceleration; Decel_2: level two deceleration; Decel_3: level three deceleration; Decel_4: level four deceleration ; PER: player efficiency rating; Usg%: usage percentage.

Table 3. Injury frequency by the different demographic variables studied.

		Injuries				
		All	No		Yes	
	Variables	N = 2577	N = 2548	%	N = 29	%
Season	Season 1	856	847	98.9	9	1.1
	Season 2	890	885	99.4	5	0.6
	Season 3	831	816	98.2	15	1.8
Month	October	90	89	98.9	1	1.1
	November	480	475	99	5	1
	December	475	466	98.1	9	1.9
	January	474	470	99.2	4	0.8
	February	371	368	99.2	3	0.8
	March	507	500	98.6	7	1.4
	April	180	180	100	0	0
Age	<25	1582	1568	98.7	20	1.3
	25-27	520	515	99	5	1
	>27	469	465	99.1	4	0.9
Court	Home	1290	1275	98.9	15	1.2
	Road	1287	1273	98.9	14	1.1
Win game	No	1227	1211	98.7	16	1.3
	Yes	1350	1337	99	13	1

Table 4. Multivariate analysis using the generalized linear mixed model for predictors of injuries in professional basketball players. This model includes minutes as an offset, and player as a random effect.

Variables	Estimate	SE	IRR (95% CI)	p-value
Intercept	-9.58	0.64		< 0.001
Deceleration_3 <3	1.47	0.45	4.36 (1.78-10.6)	0.0012
Distance ≤ 1.3	1.86	0.47	6.42 (2.52-16.3)	< 0.001
Variance of random effect (player)	2.01			

SE: standard error; IRR: Incidence rate ratio

Table 5. A classification confusion matrix for the model.

		Observed	
		No Injured	Injured
Predicted	No injured	2287	12
	Injured	261	17

The multivariate analysis using the GLMM for risk factors of injuries in professional basketball is shown in Table 4. The variables that remained significantly associated with risk of injury in the final model were a lower number of decelerations and less distance (Table 4). The player-level variance was 2.01. Based on RMSE and MAE values, the calibration model (0.10 and 0.02, respectively) was similar to the measure of the validation model (0.10 and 0.01). Given that these measures are comparable, we can conclude that there is no overfitting. The AUC value of the model showed a satisfactory performance (AUC: 0.84; 95% CI: 0.77 - 0.91), exhibiting reasonable to good discrimination. Table 5 illustrates the classification confusion matrix. As can be seen, the percentage of instances well classified was (2287+17)/2548 = 90.42%, where no-injuries are classified as acceptable. However, a low injury rate causes sensitivity to drop to lower values (58%).

Discussion

The present study investigated the relationship between tracking and non-tracking (performance) data and injuries in professional basketball. The main finding of this study was that a lower number of decelerations and less distance covered were significantly associated with injury during professional basketball games.

Related to external load (Mendez-Villanueva, 2013; Soligard et al., 2017) a few of the variables analyzed here were strongly related to injury (Ullah et al., 2012) on competition (Carling et al., 2012; Cross et al., 2016; Hulin et al., 2016; Murphy et al., 2012; Talukder et al., 2016), the variables that were significant in the multivariate analysis are quantitative. However, the correct interpretation of the statistical analysis has to be done in a multifactorial dimension (Carey et al., 2016; Colby et al., 2017; Ullah et al., 2012) and consider correlated data. The strength of the model is the association established within the variables presented. It takes into account variability of players and minutes played (used as an offset in the model). Acceleration and decelerations are two of the main variables that define basketball (Abdelkrim et al., 2007; Chaouachi et al., 2009; Maymin, 2013; Scanlan et al., 2014). Third level decelerations were found to be a risk factor: players who achieved fewer than three decelerations, and covered less than 1.3 miles were at higher risk of injury. Players undergoing lower workloads had a higher risk of injury than the rest of the roster (Gabbett, 2016; Blanch and Gabbett, 2016; Gabbett and Jenkins, 2011). Our findings of lower workloads increasing the risk of injury agree with recent findings. Despite the fact that many previous studies have analyzed the impact in the number of injuries of excessive training loads imposed on players (Caparros et al., 2016, Gabbett and Ullah, 2012) the protective effect of proper load management, as well as an adverse effect of excessively diminished training loads, have also been observed in the past (Gabbett, 2016). Adequate levels of training might have a protective effect on the athlete, also decreasing their risk of injury. The development of a minimum amount of chronic quantitative workload (distance) and acute qualitative workload (decelerations) seems an important factor to prevent injuries (Talukder et al., 2016; Soligard et al., 2017). Regarding intensities as a risk factor, a minimum amount of high-intensity decelerations per game are needed to keep the player on optimal performance (Gabbett, 2016). It might be argued that its total number can be related to the minutes that a player is on the court during the game. However, the capability to maintain higher intensities might be associated with other factors as readiness, performance, freshness, fatigue (Soligard et al., 2017) or the opponents match up. A player can achieve accelerations (Schelling and Torres, 2016), but the risk factor might be related to its capability to decelerate at higher intensities, and to how player's muscles can recover from those repeated efforts. Regarding speed parameters, same conclusions are described using GPS technology (Gabbett et al., 2013; Rossi et al., 2017).

Failure to perform high-intensity decelerations, to provide the players with a minimum cumulative distance, or to achieve adequate in-game or between-games recovery increases the chances of injury. Workload between-games (Gabbett, 2011; 2016; Gabbet et al., 2013; Purdam et al., 2015; Scanlan et al., 2014) could also be managed with this model. According to previously accumulated workloads, this value allows the modification of individual training plans on two main areas: on-court practices and strength and conditioning workouts. According to the tracking data, deceleration thresholds can be customized on the accelerometer software, having the option to manage distance and decelerations during practices. By the other hand, to identify the role of decelerations as a risk factor (as eccentric muscle action) (Hydahl and Hubal, 2014), highlights the importance of strength workouts (Pull and Ranson, 2007) and neuromuscular recovery (Hyldahl and Hubal, 2014) and its control (Mooney et al., 2013) as preventive tools.

In most sports, players are not involved in more than two games per week. However, in the professional basketball competitions observed in this study, an average of 3.4 matches were played per week for 24 weeks (Teremoto et al., 2016; Podlog et al., 2015). Therefore, the right management of player workloads is a critical strategy to avoid injuries (Drew and Finch, 2016; Gabbett, 2011; 2016) at specific periods of the season (Ferioli et al., 2018; Windt et al., 2017), and according to individual profiles. For certain players, increasing their participation in the competition is needed (Carey et al., 2016), or they may have higher chances of injury later during critical stages of the season. Acute workloads have to be specifically considered according to the players' age (Gabbett, 2016) and the period of the season. "Spikes" in workload, which are sometimes unavoidable, should be carefully controlled using individualized recovery protocols (Bengtsoon et al., 2013; Gabbett and Ullah, 2012; Hulin et al., 2013).

Decelerations are related to the ability to change direction (Tous-Fajardo et al., 2016) and are more unpredictable because they are related to opponents' matchups. A decrease in the number of decelerations can be used to identify fatigue (Lorenz and Reiman, 2011), especially in periods of accumulation of high chronic workload. A low number of them can be related to strength imbalance, and non-safe force values (Croisier et al., 2008).

Finally, at present no variables could be related to performance. Future studies investigating the relationship between player performance metrics and the overall team performance (wins or losses) are warranted.

Limitations of the study

The present study has some limitations. First, all data were obtained from public open-acces resources, potentially limiting the external validity of the results. Therefore, studies with the involvement of data coming from professional teams are needed. Second, tracking and non-tracking data were obtained during games. Data from practice sessions should be incorporated to adequately apply in-season workload plans, as suggested by Carey et al. (2017). It might offer a cause-effect relationship that could be potentially established between workload and injury on experimental designs. This limitation needs to be highlighted from the results obtained in our study. The present is an observational study; it is not an experimental design. In experimental designs, we can control factors and, thus, conclusions could establish causality, but in our current context, this is not possible. Regarding the validity of the model built, we can observe a similar strong performance metrics (AUC = 0.85) in other basketball studies (Talukder et al., 2016), even if not based on tracking parameters. Recent research on these specific parameters (Carey et al., 2017) offers similar model performance (AUC = 0.84), even is related to Australian football. Therefore, this model identifies risk factors but some limitations are suggested in a predictive level. This fact is probably due to a low injury rate and the lack of better injury definition. However, our effort tries to achieve a deeper understanding of injury prediction to several other recent studies (Bahr 2016; Carey et al., 2017; Fanchini et al., 2018; Hewett, 2017; Jovanovic, 2017; Rossi et al., 2017).

The strengths of this study are its specificity for professional basketball and the fact that it used well-established technology to identify risk factors for injury (Foster et al., 2017). However, use and applicability of technology is in some aspects sports-specific (Bangsboo et al., 2006; Gabbett and Jenkins, 2011; Hagglund et al., 2010; Hopkins et al., 2009; Hugues and Franks, 2004). Therefore, conclusions from technology-based investigations should take into account the context in which the research is conducted (Fuller, 2007; Ullah et al., 2012). Regarding methodology, a positive aspect of this study is that the model used (GLMM) tries to control for repeated measures (correlated data among the same players). Ignoring correlation of data when fitting the model may lead to biased estimates and misinterpretation of results (Casals, 2015). The study highlights the need for a correct balance between competitive schedule, team workload design and in-season recovery process. Further research should be conducted to determine how internal and external factors may be related to injury risk and performance.

Practical applications

Tracking systems, which can be easily incorporated into regular practice sessions and games, can provide useful information for the coaching staff to prevent injuries to professional basketball players. Athletes with lower external workload should be identified so that appropriate prevention strategies can be individually applied to avoid injuries.

Conclusions

Unloaded players, regarding the number of decelerations and total distance covered, have a greater risk of injury. Increasing external workload may likely reduce the risk of injury in professional basketball. More studies are needed to confirm these findings so that adequate prevention programs can be implemented to decrease the number of injuries in professional basketball and other sports.

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Key points

- The number of decelerations and the total distance can be considered risk factors for injuries in professional basketball players.
- Unloaded players have greater risk of injury compared to players with higher accumulated external workload.
- Workload management should be considered a major factor in injury prevention programs.

AUTHOR BIOGRAPHY

Toni CAPARRÓS
Employment
Strength and Conditioning coach Male Basketball Spanish National Team; Institut Nacional d'Educacio Fisica, (INEFC), University of Barcelona
Degree
PhD, BSc, MSc, MBA, MSo
Research interest
Sports performance, injury prevention, load management, elite basketball players
E-mail: info@tonicaparros.eu

Martí CASALS
Employment
Biostatistician of the National Research Centre Network for Epidemiology and Public Health (CIBERESP); Public Health Agency of Barcelona
Degree
PhD Biostatistics, Degree MS
Research interest
injury prevention, Sports medicine and Sports biostatistics
E-mail: marticasals@gmail.com

Alvaro SOLANA
Employment
Data analyst
Degree
Bachelor on Mathemathics.
Research interest
Data mining
E-mail: alvarosolana@hotmail.com

Javier PENA
Employment
Strength and Conditioning coach. Professional Basketball & Volleyball. University of Vic
Degree
PhD, BSc, MSc
Research interest
Sports performance, injury prevention, load management
E-mail: javier.pena@uvic.cat

🖂 **Toni Caparrós**
c/Sant Joan Bosco 7-9, 08338, Premià de Dalt, Barcelona, Spain