

It's a Hard-Knock Life: Game Load, Fatigue, and Injury Risk in the National Basketball Association

Melanie Lewis, PhD

Department of Psychology, University of Oklahoma, Norman

Context: National Basketball Association (NBA) athletes experience a high rate of injuries. Injury prevention requires identifying observable and controllable risk factors.

Objective: To examine the relationship among game load, fatigue, and injuries in NBA athletes.

Design: Cross-sectional study.

Setting: Game statistics and injury reports over 3 NBA seasons (2012–2015).

Patients or Other Participants: Data represented 627 players (height = 200.7 ± 8.9 cm, mass = 100.6 ± 12.1 kg, NBA experience = 4.8 ± 4.2 years, pre-NBA experience = 3.2 ± 1.9 years), 73 209 games, and 1663 injury events.

Main Outcome Measure(s): An injury event was defined as a player missing or leaving a game due to injury. Logistic multilevel regression was used to predict injuries from time-lagged fatigue and game load with between-subjects differences explained by demographic variables.

Results: The odds of injury increased by 2.87% ($P < .001$) for each 96 minutes played and decreased by 15.96%

($P < .001$) for each day of rest. Increases in game load increased injury odds by 8.23% ($P < .001$) for every additional 3 rebounds and 9.87% ($P < .001$) for every additional 3 field-goal attempts. When fatigue and game load were held constant, injury odds increased by 3.03% ($P = .04$) for each year of NBA experience and 10.59% ($P = .02$) for a 6-cm decrease in height. I observed variability in the intercepts ($P < .001$) and the slopes for minutes, rest, field-goal attempts, and rebounds (all $P < .001$).

Conclusions: Injuries were associated with greater fatigue and game load, more years of NBA experience, and being shorter than average. Both baseline injury risk and the magnitude of the load-injury and fatigue-injury associations varied across individuals. Researchers should explore the nature of these relationships.

Key Words: basketball injuries, multi-level modeling, individual differences

Key Points

- Baseline injury risk differed across players, even after controlling for years of competitive experience, height, and mass.
- The magnitude of the relationship between injury risk and performance load or fatigue differed across players.
- On average, greater performance load and fatigue, more years of National Basketball Association experience, and shorter height were associated with a higher injury risk.

For professional athletes, injuries can be life- and career-altering events, and unfortunately, researchers have shown rising trends in injury rates ranging from 12.4%¹ to 15%² within the National Basketball Association (NBA). Injuries can bring negative consequences for many stakeholders. First and foremost, overcoming injuries and regaining healthy form pose lofty challenges for athletes and can potentially interfere with their career goals.^{3–8} At one extreme, injuries requiring surgical intervention can be career ending, with as many as 39% of individuals unable to return to the NBA after Achilles tendon reconstruction³ to as few as 14% unable to return after anterior cruciate ligament (ACL) reconstruction.⁷ Some evidence has suggested a decline in the number of games⁴ and minutes per game^{3,6} played in the season after the injury by those who returned to participation after surgery compared with healthy controls. Drakos et al⁹ reported that non-season-ending injuries, such as sprains or inflammatory conditions, accounted for approximately half of the games missed due to injury, suggesting that even

minor injuries have long-term implications for players' health.

The effects of injuries also extend to the organizations with which the athletes are under contract. Regardless of the number of injured players on a team, the remaining healthy roster must continue to compete, and evidence has suggested that team performance is also affected.^{2,10} Beyond performance declines, injuries have financial repercussions for organizations. Across the league, missed games due to injuries accounted for \$344 million in player salaries in the 2014–2015 season, with specific organizations losing from \$3.5 million to \$28 million.¹¹ Efforts to identify potential associations between observable basketball game performance measures and injury risk are lacking.

Whereas little is known that might aid in reducing injury rates, researchers have learned much about specific injury prevalence, with congruent conclusions as to which injuries are most common, which injuries lead to the most time missed, and the proportion of injuries occurring during competition.^{1,9} Investigators^{3–8} have examined postopera-

tive outcomes of severe injury events and indicated that most individuals returned to sport; however, their findings were mixed regarding whether postoperative performance declined relative to preinjury performance. Other authors have shown the potential importance of fatigue^{12,13} and workload^{14,15} as injury risk factors. Last, in their epidemiologic studies, Starkey¹ and Drakos et al⁹ found no association between physical demographics and injury rates but had mixed conclusions regarding the relevance of age or experience as risk factors. Therefore, the purpose of my study was to examine the relationships among game load, fatigue, and injuries in NBA athletes. I wanted to determine whether any performance trends preceded and had the potential to predict injury events. Based on the evidence and the little that is known about injury risk, I hypothesized the following: (1) individual differences would exist in the probability of incurring 1 or more injuries during the NBA regular season, (2) higher levels of fatigue would increase the probability of sustaining an injury, (3) increases in performance load would be associated with a higher probability of injury, (4) more years of competitive basketball experience would be associated with a higher probability of injury, and (5) physical demographic differences would be unrelated to differences in injury risk.

METHODS

Datasets

The time frame for the sample was 3 NBA regular seasons from 2012 to 2015.¹⁶ A total of 433 unique players participated in the 2012–2013 season, 479 players in the 2013–2014 season, and 489 players in 2014–2015. Across all seasons, 627 players were unique, with 323 players appearing in all 3 seasons, 128 appearing in 2 seasons, and 176 appearing in 1 season. Outcomes for each player were available on a game-by-game basis, with 2 to 244 within-subject games played, resulting in a total of 73 209 observations. The game-by-game and demographic variables used in the study are described in this section.

Measures

Injury Events. Researchers^{1,9} have defined *injury* on the basis of any the following criteria: a condition that led to a missed practice or game; required referral to a physician or medication, or both; and necessitated emergent care. Information regarding missed practices, physician referrals, or medications is not publicly available, so I defined *injury* as occurring when a player left or missed a game due to a reported injury (eg, sprain, strain, fracture, contusion). This definition excluded games not played due to the coach's decision, personal reasons, or illnesses. All such information can be found in game box scores if the injury occurred before the game or news reports if the injury occurred during the game. Across the 3 seasons, the injury incidence was 2.3% (1663 injuries during 73 209 observations). Sprains were the most commonly listed type of injury, followed by soreness, strains, and bruises. The ankle was the most frequently affected injury location; other common locations were the knee, back, foot, and shoulder.

Fatigue. Conceptually, *fatigue* was defined as the depletion of mental and physical resources and was

operationally defined by accumulated time in competition with inadequate recovery time. Two variables were used to represent player fatigue: accumulated minutes in competition, which was calculated as $\frac{\Sigma \text{Minutes}}{96}$ and time lagged by 1 game, and the number of days of rest between games. In accordance with hypothesis 2, increases in accumulated minutes should have had a positive relationship with injury risk, whereas more days between games should have had a negative relationship with injury risk.

Performance Load. I chose 2 common and observable behaviors to estimate performance load: total rebounds (REBs) and field goal attempts (FGAs). *Increased performance load* was conceptually defined as the extent to which an individual performed these behaviors more than was typical. The following steps were used to calculate the estimated performance load for each athlete: (1) the season averages for REBs and FGAs were computed; (2) these season averages were used to mean center the observed game-by-game REBs and FGAs; (3) game-by-game cumulative sums of the mean-centered REBs and FGAs were calculated; and (4) all values were time lagged by 1 game (eg, the outcome for game 25 was predicted by the values for performance load and fatigue from game 24).

Demographic Variables. The demographic variables used to represent the total years of competitive experience were the total years in the NBA and in collegiate or international professional leagues (or both). The physical demographic variables were height and mass. All demographic variables were centered to each season's league-wide averages.

Statistical Model

A random-effects, multi-level logistic regression model was fit, nesting games within players and players within seasons, to predict injury outcomes. The focus of level 1 was predicting game-by-game injury outcomes, with estimated coefficients that were specific to a given player and season. Level 2 estimated average coefficients across players for a specific season, and level 3 estimated overall average effects.

Level 1. The level 1 model equation, estimating the probability of injury for game i , player j , and season t , is represented as follows:

$$\text{Injury}_{ijt} = b_{0jt} + b_{1jt} \times \text{Minutes}_{ijt} + b_{2jt} \times \text{Rest}_{ijt} + b_{3jt} \times \text{REBs}_{ijt} + b_{4jt} \times \text{FGAs}_{ijt} + r_{ijt}, \quad (1)$$

where b_{0jt} represents the intercept; b_{1jt} , b_{2jt} , b_{3jt} , and b_{4jt} represent the estimated slopes for minutes, rest, REBs, and FGAs, respectively; and r_{ijt} represents the residual.

Level 2. The following equation estimated the intercept for player j in season t :

$$b_{0jt} = \beta_{00t} + \beta_{01t} \times \text{yearsNBA}_{jt} + \beta_{02t} \times \text{pre-NBA}_{jt} + \beta_{03t} + \text{Height}_{jt} + \beta_{04t} \text{Mass}_{jt} + u_{0jt}, \quad (2)$$

where β_{00t} represents the average intercept for season t across all players; β_{01t} represents the average effect of years in the NBA on the intercept across players for season t ; β_{02t} represents the average effect of pre-NBA competitive experience; β_{03t} and β_{04t} represent the average effects of height and mass, respectively; and u_{0jt} represents the

residual term for player j in season t and has a mean of zero and a variance of τ_{x00} .

The remaining level 2 equations follow:

$$b_{1jt} = \beta_{10t} + u_{1jt} \quad (3)$$

$$b_{2jt} = \beta_{20t} + u_{2jt}, \quad (4)$$

where β_{10t} and β_{20t} represent the average slopes for minutes and rest, respectively, across players in season t and u_{1jt} and u_{2jt} are the residuals for player j in season t , respectively, with means of zero and respective variance terms τ_{x11} and τ_{x22} .

$$b_{3jt} = \beta_{30t} + u_{3jt} \quad (5)$$

$$b_{4jt} = \beta_{40t} + u_{4jt}, \quad (6)$$

where β_{30t} and β_{40t} represent the average slopes for REBs and FGAs, respectively, across players in season t and u_{3jt} and u_{4jt} are the residuals for player j in season t , respectively, with means of zero and respective variance terms τ_{x33} and τ_{x44} .

Level 3. The values at level 3 represented the average estimates across all players and all seasons. All effects at level 3 were treated as fixed. As such, the equations are simple substitutions:

$$\beta_{00t} = \gamma_{000} \quad (7)$$

$$\beta_{01t} = \gamma_{010} \quad (8)$$

$$\beta_{02t} = \gamma_{020} \quad (9)$$

$$\beta_{03t} = \gamma_{030} \quad (10)$$

$$\beta_{04t} = \gamma_{040} \quad (11)$$

$$\beta_{10t} = \gamma_{100} \quad (12)$$

$$\beta_{20t} = \gamma_{200} \quad (13)$$

$$\beta_{30t} = \gamma_{300} \quad (14)$$

$$\beta_{40t} = \gamma_{400}, \quad (15)$$

where γ_{000} is the overall average intercept, γ_{010} and γ_{020} are the main effects of years of competitive experience on differences in baseline injury risk, γ_{030} and γ_{040} are the main effects of physical differences on baseline injury risk, γ_{100} and γ_{200} represent the overall average relationship between fatigue and injury outcomes, and γ_{300} and γ_{400} represent the overall average relationship between performance load and injury outcomes.

Tests of Hypotheses

The between-subjects intercept variance, τ_{x00} , from Equation 2 tested hypothesis 1. A difference in the variance of the intercepts indicated differences in the baseline probability of incurring an injury even after controlling for all other effects. I used the fixed effects for accumulated minutes (γ_{100}) and rest (γ_{200}) to test hypothesis 2, indicating

the strength and direction of the relationship between fatigue and the probability of injury. To test hypothesis 3, I used the fixed effects for REBs (γ_{300}) and FGAs (γ_{400}), which indicated the strength and direction of the relationship between performance load and the probability of injury. Hypothesis 4 was tested by the main effects for years of NBA (γ_{010}) and pre-NBA (collegiate or international; γ_{020}) experience, which indicated how much the baseline injury risk changed per year of NBA and pre-NBA experience. Finally, to test hypothesis 5, I used the main effects for height (γ_{030}) and mass (γ_{040}), which represented the degree to which baseline injury risk changed due to differences in height or mass. The α level was set at .05. All analyses were conducted with SAS (version 9.2; SAS Institute, Inc, Cary, NC).

RESULTS

The overall ability of the model to predict injuries was evaluated using the area under the curve. An area under the curve value of 0.5 is equivalent to a coin toss, or random chance, and 1.0 is perfect prediction of the outcome. The random-effects, multi-level model produced an area under the curve of 0.9296 ± 0.002 , suggesting that this model provided good discrimination between injury and noninjury events. Furthermore, a cutoff-predicted probability of injury value equal to 0.02 had a sensitivity of 80.9% and specificity of 86.4%, leading to a positive predictive value of 12.16% and a negative predictive value of 99.49%. Exploring these predicted values suggested a positive correlation ($r = 0.672$) between the average probability of injury for a given player and his total injury events in that season. The average predicted probability of injury across players who sustained at least 1 injury was 0.042 compared with an average of 0.003 for those who remained healthy. Table 1 displays the descriptive statistics for the independent variables. Tables 2 and 3 display the estimates for the fixed and random effects.

Hypothesis 1

The first hypothesis stating that differences would exist in baseline injury risk across players was supported ($\tau_{x00} = 2.9314$, $P < .001$). The average intercept across all players was -4.4754 ($P < .001$). In other words, the average probability of injury in game 1 for players of average years of competitive experience, height, and mass was 0.011. Of the 627 players in the dataset, 26.5% ($n = 166$) had estimated intercepts that differed from average in at least 1 season. As hypothesized, between-subjects intercept differences remained even after controlling for demographics, fatigue, and performance load.

Hypothesis 2

Both main effects for accumulated minutes ($\gamma_{100} = 0.0283$, $P < .001$) and days of rest ($\gamma_{200} = -0.1739$, $P < .001$) supported the second hypothesis that greater fatigue would be related to higher injury risk. Every additional 96 minutes played was associated with a 2.87% increase in the odds of injury, holding other variables constant. For each additional day of rest between games, the odds of injury decreased by 15.96%, holding other variables constant. Whereas the estimated fixed effects supported the hypoth-

Table 1. Descriptive Statistics for Independent Variables (Mean \pm SD)

Label	Group		
	Full Sample (N = 1401)	No Injury (n = 605)	Injury (n = 796)
Accumulated min (scaled per 96)	8.27 \pm 6.77	8.23 \pm 6.76	9.72 \pm 7.11
Rest	1.25 \pm 1.20	1.25 \pm 1.20	1.19 \pm 1.06
Rebounds (scaled per 3) ^a	-0.50 \pm 4.74	-0.52 \pm 4.75	0.43 \pm 4.16
Field goal attempts (scaled per 3) ^a	-1.31 \pm 7.72	-1.35 \pm 7.73	0.35 \pm 6.64
NBA experience, y ^b	4.75 \pm 4.20	3.99 \pm 4.28	5.33 \pm 4.05
Pre-NBA experience, y ^b	3.17 \pm 1.94	3.44 \pm 1.85	2.97 \pm 1.98
Height, cm ^b	200.73 \pm 8.86	200.66 \pm 8.82	200.78 \pm 8.90
Mass, kg ^b	100.61 \pm 12.14	99.96 \pm 11.81	101.11 \pm 12.37

Abbreviation: NBA, National Basketball Association.

^a Centered to players' average.

^b Analysis was conducted after centering to these full-sample values.

esis, variability existed across players in both the main effect of minutes ($\tau_{x11} = 0.0171$, $P < .001$) and rest ($\tau_{x22} = 0.1971$, $P < .001$). Specifically, I observed differences in the estimated effect of accumulated minutes in 12.6% ($n = 76$) of individuals and an effect of rest in 10.7% ($n = 67$).

Hypothesis 3

Increases in performance load, as represented by REBs ($\gamma_{300} = 0.0791$, $P < .001$) and FGAs ($\gamma_{400} = 0.0941$, $P < .001$), were associated with higher injury risk, supporting hypothesis 3. If the performance load was 3 REBs above the player's average, the odds of injury increased by 8.23%. Similarly, an increase of 3 FGAs relative to the player's average was associated with a 9.87% increase in the odds of injury. Furthermore, I observed differences across players for the main effect of REBs ($\tau_{x33} = 0.1233$, $P < .001$) and FGAs ($\tau_{x44} = 0.0532$, $P < .001$). Although hypothesis 3 was supported, the caveat is that variability existed among players in the magnitude of the relationship between performance load and injury risk. From the sample, 14.7% ($n = 92$) differed from average for the effect of FGA load and 10.5% ($n = 66$) for the REB load effect.

Hypothesis 4

Of the 2 measures representing competitive experience, only years of NBA experience explained baseline differences in injury risk ($\gamma_{010} = 0.0298$, $P = .04$). This suggested that for 2 otherwise similar players, the odds of an injury event on game 1 were 3.03% higher for the player with 1 additional year of NBA experience. I did not observe an effect for years of pre-NBA experience ($\gamma_{020} = -0.0241$, P

$= .43$). On the basis of these results, hypothesis 4 was only partially supported.

Hypothesis 5

Hypothesis 5, that physical demographic differences would be unrelated to injury risk, was partially supported. I observed an effect for height ($\gamma_{030} = -0.1119$, $P = .02$) but not for mass ($\gamma_{040} = 0.0689$, $P = .17$). For 2 similar players, the odds of injury in game 1 were 10.59% lower for a player who was 6-cm taller than an otherwise similar player.

DISCUSSION

Player health is of the utmost importance. The goal of my study was to make an empirical contribution to maintaining the health of athletes by identifying the important antecedents associated with injuries. Many investigators have explored postinjury outcomes, but less attention has been paid to prevention. Using multilevel modeling enabled me to quantify and parse the undeniable contribution of individual differences to injury outcomes such that the average effects of fatigue and performance load could be estimated. Furthermore, this approach enabled testing the extent to which demographic information explained individual differences. On average, higher levels of fatigue and workload led to greater injury risk, and with those factors held constant, a higher injury risk was associated with being above average in years of NBA experience and being below average in height.

The positive association between fatigue and injury risk was in accordance with results from research on elite soccer¹⁵ and rugby¹² players. Accumulated minutes and a

Table 2. Fixed-Effects Multi-Level Model Predicting Injury Outcomes

Effect	Label	Estimate	<i>t</i> Value	<i>P</i> Value	Odds Ratio	95% Confidence Limits
γ_{000}	Intercept	-4.4754	-64.45	<.001 ^a	NA	NA
γ_{100}	Accumulated minutes	0.0283	4.47	<.001 ^a	1.029	1.016, 1.042
γ_{200}	Rest	-0.1739	-7.84	<.001 ^a	0.840	0.805, 0.878
γ_{300}	Rebounds	0.0791	4.83	<.001 ^a	1.082	1.048, 1.118
γ_{400}	Field goal attempts	0.0941	8.98	<.001 ^a	1.099	1.076, 1.122
γ_{010}	NBA experience	0.0298	2.06	.04 ^a	1.030	1.001, 1.060
γ_{020}	Pre-NBA experience	-0.0241	-0.79	.43	0.976	0.967, 1.036
γ_{030}	Height	-0.1119	-2.35	.02 ^a	0.894	0.814, 0.982
γ_{040}	Mass	0.0689	1.32	.17	1.071	0.967, 1.187

Abbreviations: NA, not applicable; NBA, National Basketball Association.

^a Indicates difference ($P < .05$).

Table 3. Multilevel Model Random Effects Predicting Injury Outcomes

Effect	Label	Estimate	z Value	P Value
τ_{x00}	Intercept variance	2.9314	14.95	<.001 ^a
τ_{x11}	Accumulated minutes variance	0.0171	10.00	<.001 ^a
τ_{x22}	Rest variance	0.1971	8.00	<.001 ^a
τ_{x33}	Rebounds variance	0.1233	8.91	<.001 ^a
τ_{x44}	Field-goal attempts variance	0.0532	9.42	<.001 ^a

^a Indicates difference ($P < .05$).

lack of rest days did not directly cause injuries, and researchers should examine the causal pathways linking fatigue to injuries, particularly given the variability in the estimated effects of these variables. In their investigation of knee injuries, Goitz et al¹³ reported that knee-joint proprioception errors were greater during a state of fatigue and specifically suggested that the mechanism for ACL injuries is more likely to occur in fatigued states. Future studies linking mechanisms of various common basketball injuries with controllable risk factors are important steps toward improving player health outcomes.

On average, increases in performance load were positively associated with higher injury risk. Similarly, one could interpret the results as reductions in performance load being associated with a lower injury risk. However, I observed variability in the strength of this effect across players. In their study of training load for football players, Nassis and Gabbett¹⁴ reported similar results, with an additional conclusion that progressive increases in workload led to resilience against injury risk. Researchers should investigate the relationship between the rate of increases in performance load and injury risk to identify whether similar patterns are present in basketball players. Such examinations may help explain

the variability of the workload-injury association found across the individuals in my study.

Epidemiologic studies^{1,9} have produced mixed conclusions regarding the association between age or experience and injury rates. Given the existing uncertainty, I was not surprised that hypothesis 4 was not fully supported. Only the duration of a player's NBA career explained the variability in baseline injury risk. This suggests that, after controlling for differences in fatigue and performance load, having more NBA experience than the league-wide average (4.7 years) increased the injury risk, but years spent in collegiate or international competition had no effect. Physical wear and tear is typically correlated with age; however, based on the current study, a 25-year-old athlete who played for 4 years in college and is entering his third year in the NBA would have a lower injury risk than a 25-year-old athlete who is entering his sixth year in the league after playing 1 year in college. Given that collegiate and international teams play approximately 30-game regular seasons and NBA teams play 82-game seasons, a potential interpretation of these results is that overuse, not age, is implicated in injury risk, but only further research can support such conclusions.

Regarding physical differences, authors of epidemiologic research^{1,9} have reported no correlations between physical characteristics and general injury rates, but I found that being taller was associated with a lower injury risk. Further investigation into these physical risk factors is warranted before strong conclusions can be made.

One limitation of my study was the reliance on public injury data, which is not necessarily accurate, specific, or inclusive of all injuries that occurred over the course of a given season. Given the data-collection method, an additional limitation was that no differentiation was made among the injury types. Researchers should determine whether these results can be generalized across injury types

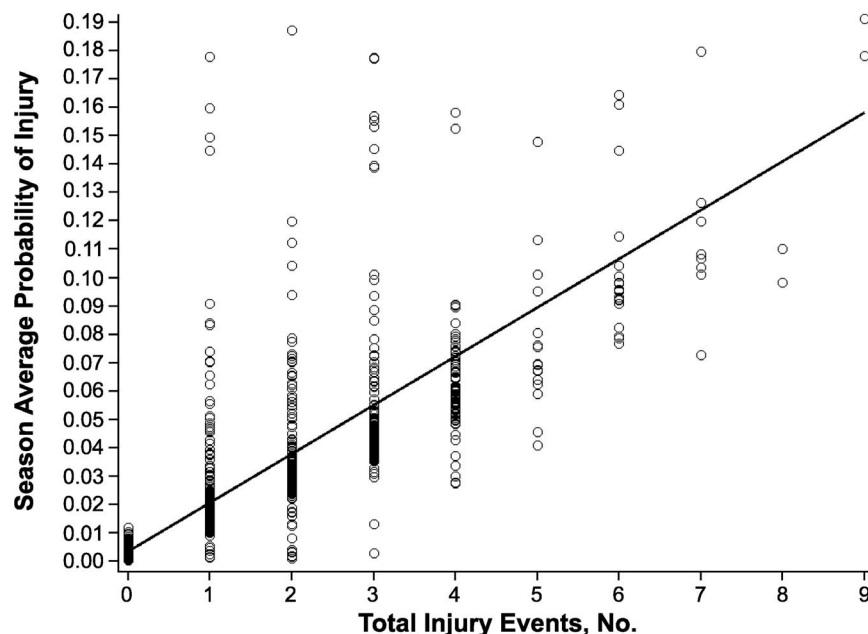


Figure. The relationship between a player's average predicted probability of injury and total injury events in a given season. Each circle represents an individual player.

or if different pathologic conditions have different risk factors. In the medical research focused on specific pathologic conditions,^{3–8} authors of all but one⁸ study matched the injured sample to healthy controls of similar demographics, but the physical characteristics of the samples were not constant across these studies. For example, in their study conducted on outcomes after lumbar discectomy, Anakwenze et al⁴ indicated that 50% of their sample played the center position, whereas in their study conducted on outcomes after microfracture surgery, Cerny et al⁶ assessed a sample in which only 12.5% of the injured athletes played at the center position. Similarly, of those who had ACL ruptures, the average mass was approximately 214 lbs (96.3 kg),⁵ whereas Anakwenze et al⁴ studied a sample with an average mass of around 236 lbs (106.2 kg). This might indicate that different physical characteristics are associated with specific types of injuries and the effect of fatigue and performance load on specific injury risk might vary.

PRACTICAL IMPLICATIONS FOR INJURY PREDICTION AND PREVENTION

Across the 3 seasons studied, 56.8% of players ($n = 248$ of 433 in 2012–2013, $n = 272$ of 479 in 2013–2014, $n = 276$ of 489 in 2014–2015) had at least 1 injury event, and on average, these individuals had a predicted probability of injury equal to 0.042 (range, 0.000001–0.953). For players who did not sustain any injuries, the average predicted probability of injury was equal to 0.003 and the maximum observed probability never exceeded 0.013. As shown by the high negative predictive value (99.49%) for the cutoff of 0.02, one can be confident that, if the probability of injury is less than 2%, no injury will occur. On the other hand, the low positive predictive value (12.16%) would suggest a high false-positive rate; however, across all players who sustained at least 1 injury, 97.9% exceeded the 0.02 cutoff at some point in the season in which they sustained an injury.

Beyond distinguishing players with no injuries from players who experienced at least 1 injury, the average predicted probability was positively correlated ($r = 0.672$) with the total number of injury events, as can be seen in the Figure.

Whereas my study was limited because I did not differentiate between minor and season-ending injuries, the differences in distributions of these estimated probabilities illustrates the importance of fatigue, performance load, years of competitive experience, and physical demographics as predictors of injury outcomes. Injuries are infrequent events, and as such, the cutoff value of 0.02 could serve as a tool for identifying which players should be monitored more closely and which are currently at less risk for sustaining an injury.

Performance load can increase or decrease injury risk, and players who carry a heavier load for too long are more likely to get hurt. However, compliance with a recommendation such as rebounding or shooting the ball less is unlikely to be high. Furthermore, increases in load may be due to external factors, such as an injury to a teammate. Monitoring performance load can be helpful for assessing injury risk, but the use of this information to prevent injuries may be limited.

Accumulated minutes had the smallest relationship with injury risk, suggesting that restricting the number of

minutes played may not be a useful method for preventing injuries for the average player. On the other hand, rest showed the strongest effect of all the variables studied. Simply not playing in back-to-back games can reduce the probability of an injury by almost 16% for the average player. Whereas the topic of player rest is becoming increasingly controversial for basketball fans and the media, the data support its utility in preventing injuries.

Reducing injury risk is a complex concern. Demographic risk factors cannot be changed, and perhaps the most important finding from this study was individual differences in the relative importance of minutes, rest, and performance load. For this reason, no “one-size-fits-all” solution to injury prevention is available, and general recommendations should be considered in relation to the expert judgment of the health professionals familiar with the athletes under their care.

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Address correspondence to Melanie Lewis, PhD, Department of Psychology, University of Oklahoma, 455 West Lindsey Street, Norman, OK 73019. Address e-mail to melielewis@ou.edu.