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Tracking What Truly Matters: The Contribution of Game Load, Recovery, and Well-Being to Basketball Performance

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Purpose: This study aimed to explore the relationships of game load, recovery status, and well-being with performance efficiency in basketball players across different performance levels. ***Methods:*** Data from 16 professional male basketball players across 18 official basketball games were analyzed utilizing principal component analysis to reduce dimensionality and identify key factors related to game load, perceived recovery, and well-being associated with performance. Quantile regression was employed to assess the impact of these factors on performance efficiency at different quantiles (10th, 50th, and 90th). ***Results:*** Six factors were extracted. The first factor, composite load (a combined measure of the external physical loads and session rating of perceived exertion experienced by players), explained 42% of the variance, followed by well-being (15%), composite jump load (focused on jump-related movements, 11%), PlayerLoad per minute (5%), muscle soreness (4%), and recovery status (4%). Quantile regression analyses revealed that composite load had a significant positive effect in the ordinary least-squares estimate ($P < .001$) and at the 10th ($P = .044$) and 50th quantiles ($P < .001$). Composite jump load had significant effects in the ordinary least-squares estimate ($P < .001$) and the 50th quantile ($P = .003$). PlayerLoad per minute had significant effects in the ordinary least-squares estimate ($P < .001$) and in both the 10th ($P < .001$) and the 50th quantiles ($P < .001$). In addition, well-being was significant at the 50th quantile ($P < .001$), whereas muscle soreness and recovery showed no significant effects. ***Conclusion:*** Composite load and PlayerLoad per minute consistently had positive associations with game performance, particularly for players at low and medium performance levels.

Keywords: efficiency, microsensor, perceptual rating, quantile regression, principal component analysis, game-related statistics

The performance of elite athletes, particularly in team sports such as basketball, is influenced by a complex interplay of physical, psychological, and technical factors.[1] Within sport-science contexts, the ability to quantify and analyze these multifaceted factors has become increasingly critical.[2] The advent of advanced motion tracking systems, physiological monitoring tools, and sophisticated data analytics has enabled a more granular examination of factors that drive performance, providing researchers and practitioners with insights necessary to optimize training and competition strategies.[3] In this regard, the use of various technologies and approaches to measure the external and internal loads encountered by basketball players is highly sought by practitioners.[4]

In recent years, quantifying the relationships between external and internal load variables and game performance in basketball has gained increased research attention.[5–7] For instance, total distance covered per minute ($r = .13$) along with high-intensity decelerations (DEC) per minute ($r = -.03$) and total accelerations (ACC) per minute ($r = -.03$) during games among professional male basketball players presented relatively weak associations with performance index rating (PIR, a commonly used basketball metric that combines several individual performance indicators, such as points scored, assists, rebounds, steals, blocks, and turnovers, to provide a comprehensive evaluation of a player's overall contribution to the game).[6] In addition, PlayerLoad per minute (PL·min^{-1}) showed significant moderate associations with field goal accuracy ($r = .41$) and points scored ($r = .54$) during games in female collegiate basketball players.[7] Likewise, PL·min^{-1} ($r = .13$) and high-intensity inertial movement analysis (IMA) events per minute ($r = .13$) exhibited small positive associations with player efficiency, whereas internal load variables (rating of perceived exertion [RPE] and session RPE [sRPE]) showed small negative associations ($r = -.04$ and $-.08$) with player efficiency during games with semiprofessional male basketball players.[5] Although these studies provide valuable insights, the inconsistent associations between external and internal load variables and game performance suggest that clear underlying relationships are yet to be definitively elucidated. Therefore, further research is needed to clarify how external and internal loads independently and collectively influence performance outcomes.

The lack of clear relationships established between load and performance variables during basketball games in the literature supports other factors holding potential contributions. Indeed, perceptually based, athlete-reported outcome measures provide

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useful insight into how players are coping with various stressors and their readiness to perform in competition.[8] Performance in team sports is inherently multifaceted, shaped not only by the external demands placed on athletes and their physiological responses but also by psychological dimensions, including perceived well-being and recovery status. Although varied relationships have been reported between perceptual measures and performance-based outcomes in team sport athletes,[8] perceived recovery status[9] and well-being[4] are popular perceptual measures gathered in practice, with their impact on performance being somewhat investigated in basketball players.[9] For example, strain, computed by multiplying the total weekly load by the monotony score, was found to significantly contribute ($r = .22$) to game performance (GameScore) in female collegiate basketball players.[10] In contrast, nonsignificant ($P > .05$, trivial-to-small effects) differences in PIR during games were reported between player clusters representing low, medium, and high pregame recovery status in semiprofessional male basketball players.[11] These collective findings underscore the varied impact of game load, recovery status, and well-being on game performance reported across basketball players.

Although associations between external and internal load, recovery status, and well-being with performance have been provided in isolation within basketball contexts, no studies have examined how they contribute to game performance in combination. Furthermore, most research[5–7] has relied on traditional correlation and regression methods to quantify associations across entire teams, which does not capture the varying impacts of these factors across players at different performance levels. To address this gap, innovative statistical approaches are needed, such as combining principal component analysis (PCA) with quantile regression (QR). PCA facilitates the extraction of key factors from a large set of load and perceptual variables by reducing their dimensionality. In turn, QR provides a more detailed analysis by examining how extracted factors are related to basketball performance across various player quantiles predicated on their individual performance levels. Use of such an integrated statistical framework will provide deeper understanding of how these factors influence game performance specifically in players at varied performance levels. Therefore, the aims of this study were to (1) examine the contribution of external and internal load, perceived recovery status, and well-being to basketball performance and (2) determine how these factors interact to influence player performance at various individualized performance levels.

Methods

Subjects

A total of 16 professional male basketball players were recruited for this study (mean [SD]: age: 27.2 [1.4] y, height: 198.4 [6.3] cm, body mass: 98.4 [12.7] kg). All players were from the same team competing in the Chinese National Basketball League, a second-tier, professional-level competition. Inclusion criteria required familiarity with all procedures, including digital questionnaires and wearable devices, as well as consistent game participation. All players included in the study were medically cleared for participation, having undergone thorough physical examinations to ensure the absence of any injuries or medical conditions that could affect their performance or safety during the study. Exclusion criteria included preexisting injuries or medical conditions and playing fewer than 15 minutes in each individual game. Players were made aware of the benefits and risks of participation before providing written informed consent prior to participation. Study procedures were approved by Tsinghua University's Institutional Review Board, following the Helsinki Declaration (IRB20230207).

Design

This longitudinal observational study was conducted from June 15, 2024, to August 19, 2024, covering games 2 through 20 of the 25-game regular season in the competition. Based on prior research,[12] a power analysis using G*Power (version 3.1.9.6) and inputting an effect size of 0.25, an alpha level of .05, and a statistical power of 0.80 estimated a minimum of 62 observations for linear multiple regression model. With an average of 6 players contributing data in each individual game (ie, playing at least 15 min), 11 games were deemed necessary to meet the required sample size. However, to ensure sufficient data coverage and account for potential data loss, 18 games were ultimately collected. Each game consisted of four 10-minute quarters, with playing time during games determined inclusive of stoppages (eg, out of bounds, fouls) but excluding rest periods (ie, substitutions, time-outs, and interquarter breaks).

Procedures

External- and Internal-Load Measurement

Each player wore a Catapult S7 device (Catapult Innovations) to monitor their external load during games. These devices were equipped with a 100-Hz triaxial accelerometer, gyroscope, and magnetometer and were positioned between the scapulae at the level of the C7-T1 vertebrae using a manufacturer's vest.[13] PL (arbitrary units) was determined as a key external load variable, which was derived from the accelerometer data. PL was calculated as an absolute value and relative to playing time in games ($PL \cdot min^{-1}$). After each game, data were downloaded and exported at 100 Hz as instantaneous PL, representing the square root of the change in acceleration across the transverse (x), coronal (y), and sagittal (z) planes, calculated using proprietary software (OpenField version 3.10.5, Catapult Innovations) via the following formula: $PL = [\sqrt{\ } (Ac1n - Ac1n\text{-}1)^2 + (Ac2n - Ac2n\text{-}1)^2 + (Ac3n - Ac3n\text{-}1)^2] \times 0.01$, where Ac1, Ac2, and Ac3 are the orthogonal components measured by the triaxial accelerometer, and 0.01 is the scaling factor.[14] The reliability of PL has been previously provided in team sport contexts with coefficients of variation ranging between 0.9 and 1.9%.[15,16]

IMA variables were also captured from devices to further represent external load. IMA variables were categorized by the directional movement of players, including ACC (–45° to 45°), DEC (−135° to 135°), changes of direction (COD) to the left (−135° to –45°), and COD to the right (45° to 135° and intensity at which they were performed [low: 1.5–2.5 $m \cdot s^{-2}$, medium: 2.5–3.5 $m \cdot s^{-2}$, and high: >3.5 $m \cdot s^{-2}$]). Jumps were detected as an additional IMA variable in the vertical direction using a proprietary algorithm within the software and classified as low-intensity, medium-intensity, and high-intensity events using jump height cutoffs of <20 cm, 20 to 40 cm, and >40 cm, respectively. Notably, low-intensity ACC, DEC, and COD events were excluded from the final analysis to ensure the focus remained on physically demanding actions that are more relevant to performance outcomes in basketball, whereas low-intensity vertical jumps were retained because they involve lower-limb coordination and explosiveness, crucial for actions like rebounding and shot blocking.[17] The thresholds adopted for IMA variables aligned with the most commonly adopted approaches using microsensor technology in the basketball literature as identified in a recent review.[18] All IMA variables were determined as a count, with IMA events tabulated overall, separately for medium-intensity and high-intensity movements, and separately for medium-intensity and high-intensity explosive actions.[19,20] The reliability for IMA-derived external load variables has been determined previously, with coefficients of variation ranging between 3.1% and 6.7% in team sport settings.[21]

To assess internal load, players reported individualized RPE using the modified CR-10 scale[22] approximately 15 to 30 minutes following each game. This method has been widely used across team sports for quantifying internal load, correlating strongly with objective, internal physiological measures such as blood lactate concentration and heart rate.[23] sRPE data were collected via an online survey platform (Google Forms).

Perceived Recovery Status and Well-Being Measurement

Perceived recovery status was measured using the Total Quality Recovery scale (6 = "very poor recovery" to 20 = "very good recovery").[24] The Total Quality Recovery scale provides an efficient, practical method for monitoring recovery between games or training sessions, with studies confirming its reliability, validity, and correlations with physiological recovery and performance markers.[25] Players provided their Total Quality Recovery ratings before the warm-up phase prior to games.[26] In turn, player well-being was determined using an established online questionnaire tailored for basketball players.[27] The questionnaire evaluated key dimensions considered important for well-being, including fatigue, sleep quality, muscle soreness, stress levels, and mood, using a 5-point Likert-type scale with scores ranging between 1 and 5 in increments of 0.5 points.[28] The total well-being score was derived by summing the individual scores of the 5 items assessed, providing a comprehensive measure of overall well-being. Well-being data were consistently collected each morning before 10:00 on game day via an online survey platform (Google Forms).[29,30]

Game Performance Measurement

Game-related statistics were collected during all 18 official games by a certified basketball coach experienced in basketball statistics and notational analysis, using the Catapult Vision system (Catapult Innovations). These statistics were used to determine the PIR for each player in each game, which has been widely used as a performance indicator in basketball research.[5–7,31–33] PIR was calculated using the following formula: (points + rebounds + assists + steals + blocks + fouls drawn) − (missed field goals + missed free-throws + turnovers + shots blocked + fouls committed).[34] To normalize data relative to individual playing time, PIR values were adjusted by dividing each PIR score by the live clock time that each player spent on the court per game (minutes played excluding stoppages and breaks). For instance, a PIR of 15 achieved over 30 minutes of live gameplay resulted in an adjusted PIR of 0.5. This adjustment enabled a standardized comparison of player performances based on active playing time, providing a more precise measure of impact per minute of actual gameplay.[6]

Statistical Analysis

All data are expressed as mean (SD). The normality of all data was verified using the Shapiro–Wilk test. PCA with varimax rotation was used for data reduction. A Bartlett test of sphericity was computed to check for significant correlations among variables, and the Kaiser–Meyer–Olkin measure was used to evaluate the suitability of factor analysis, with values above 0.50 indicating adequacy.[35] In PCA, component retention was guided by 3 criteria: Kaiser rule (eigenvalues > 1); components explaining at least 80% of the total variance; and model fit assessed by comparing reproduced and observed correlations, with fewer than 50% differing by more than 0.05.[35–37] In turn, factor loadings greater than 0.60 were considered substantial, indicating that the corresponding variables meaningfully contributed to the interpretation of the principal component.[35]

QR was utilized to investigate the associations between extracted factors and game performance (PIR) across distinct quantiles of the PIR distribution, with specific emphasis on the 10th, 50th, and 90th quantiles.[38–40] The 10th, 50th, and 90th quantiles were selected to investigate the effects of extracted factors across low, medium, and high levels of game performance (PIR), providing a comprehensive view of how these factors influenced performance across a sufficient distribution.[39] The results were compared with ordinary least squares (OLS) estimates to assess consistency and identify heterogeneity in the effects.[41,42] Coefficients were reported with 95% confidence intervals (CIs), and sensitivity analyses ensured the robustness of findings.[43]

All analyses were performed using R Studio (version 3.5.3, R Foundation for Statistical Computing). Correlation analyses were conducted using the "rmcorr" package. PCA was conducted using the "FactoMineR" and "factoextra" packages, and OLS and QR were performed with the "quantreg" package. Statistical significance was set at $P < .05$.

Results

Descriptive data for all variables are presented in Table 1. Bartlett test ($\chi^2 = 3925.68$, $P < .001$) and the Kaiser–Meyer–Olkin measure (0.636) confirmed suitability of the data set for PCA, as shown in Table 2. Six factors (rotated components) were extracted, accounting for 83% of the total variance, indicating effective dimensionality reduction. Figure 1 presents the rotated components loadings of each variable for the 6 factors. Specifically, the first factor, "composite load" (sRPE, PL, medium-intensity ACC, high-intensity ACC, medium-intensity DEC, high-intensity DEC, medium-intensity left COD, high-intensity left COD, medium-intensity right COD, high-intensity right COD, medium-intensity explosive actions, high-intensity explosive actions, medium-intensity IMA events, high-intensity IMA events), explained 42% of the total variance; the second factor, well-being, explained 15%; the third factor, "composite jump load" (total jumps, low-intensity jumps, and medium-intensity jumps), explained 11%; the fourth factor, PL·min^{-1}, accounted for 5%; the fifth factor, muscle soreness, represented 4%; and the sixth factor, perceived recovery, accounted for the remaining 4%.

The QR results presented in Table 3 and Figure 2 provided insight into the contribution of various principal components to game performance across different quantiles (10th, 50th, and 90th) as well as a comparison with OLS estimates. The first factor, "composite load" showed a significant effect in the OLS estimate (beta = 0.22; 95% CI, 0.10–0.35; $P < .001$) as well as at the 10th quantile (beta = 0.13; 95% CI, 0.01–0.25; $P = .044$) and 50th quantile (beta = 0.32; 95% CI, 0.15–0.50; $P < .001$). The second factor, well-being, had a significant effect at the 50th quantile (beta = 0.39; 95% CI, 0.18–0.60; $P < .001$). The third factor, "composite jump load," showed a significant effect in the OLS estimate (beta = 0.52; 95% CI, 0.23–0.81; $P < .001$) and at the 50th quantile (beta = 0.65; 95% CI, 0.23–1.08; $P = .003$). The fourth factor, PL·min^{-1}, had a significant effect in the OLS estimate (beta = 1.77; 95% CI, 0.96–2.58; $P < .001$) as well as at the 10th quantile (beta = 1.88; 95% CI, 0.90–2.86; $P < .001$) and 50th quantile (beta = 1.93; 95% CI, 1.02–2.85; $P < .001$).

Table 1 Descriptive Statistics of Game Load, Perceived Recovery, and Well-Being Variables in Professional Male Basketball Players

Variable	Mean (SD)
Internal load	
sRPE, AU	125.25 (7.85)
External load	
PL·min^{-1}, AU·min^{-1}	10.87 (1.33)
PL, AU	297.18 (127.82)
Total jumps, counts·min^{-1}	1.17 (0.46)
Low-intensity jumps, counts·min^{-1}	0.52 (0.32)
Medium-intensity jumps, counts·min^{-1}	0.40 (0.18)
High-intensity jumps, counts·min^{-1}	0.24 (0.13)
Medium-intensity ACC, counts·min^{-1}	0.36 (0.15)
High-intensity ACC, counts·min^{-1}	0.27 (0.12)
Medium-intensity DEC, counts·min^{-1}	0.53 (0.19)
High-intensity DEC, counts·min^{-1}	0.25 (0.12)
Medium-intensity left COD, counts·min^{-1}	0.89 (0.27)
High-intensity left COD, counts·min^{-1}	0.32 (0.13)
Medium-intensity right COD, counts·min^{-1}	0.98 (0.29)
High-intensity right COD, counts·min^{-1}	0.34 (0.15)
Medium-intensity explosive actions, counts·min^{-1}	2.76 (0.58)
High-intensity explosive actions, counts·min^{-1}	1.19 (0.33)
Medium-intensity IMA events, counts·min^{-1}	3.17 (0.61)
High-intensity IMA events, counts·min^{-1}	1.43 (0.38)
Recovery status	
Recovery, AU	12.10 (1.76)
Wellness	
Fatigue, AU	2.64 (0.64)
Sleep, AU	3.31 (1.08)
Muscle soreness, AU	2.83 (0.72)
Stress, AU	2.81 (0.67)
Mood, AU	3.60 (0.71)
Well-being, AU	15.20 (2.87)

Abbreviations: ACC, accelerations; AU, arbitrary units; COD, changes of direction; DEC, decelerations; IMA, inertial movement analysis; PL, PlayerLoad; sRPE, session rating of perceived exertion.

Table 2 Descriptive Statistics of the Component, Bartlett Test of Sphericity, and KMO Measure of Sampling Adequacy of the Factor Analysis (Principal Component Methods With Varimax Rotation)

	Factor					
Eigen value	**RC1**	**RC2**	**RC3**	**RC4**	**RC5**	**RC6**
Sum of squared loadings	10.89	3.91	2.98	1.36	1.17	1.16
Proportion variance	0.42	0.15	0.11	0.05	0.04	0.04
Cumulative variance	0.42	0.57	0.68	0.74	0.78	0.83
Bartlett test of sphericity						
χ^2	3925.68					
P	<.001					
KMO	0.636					

Abbreviations: ACC, accelerations; COD, changes of direction; DEC, decelerations; IMA, inertial movement analysis; KMO, Kaiser–Meyer–Olkin. Note: RC1, composite load (including session rating of perceived exertion, PlayerLoad, medium-intensity ACC, high-intensity ACC, medium-intensity DEC, high-intensity DEC, medium-intensity left COD, high-intensity left COD, medium-intensity right COD, high-intensity right COD, medium-intensity explosive actions, high-intensity explosive actions, medium-intensity IMA events, and high-intensity IMA events); RC2, well-being; RC3, composite jump load (including total jumps, low-intensity jumps, and medium-intensity jumps); RC4, PlayerLoad per minute; RC5, muscle soreness; RC6, recovery.

Discussion

The primary objective of this study was to investigate the contribution of game load, perceived recovery status, and well-being to in-game basketball performance, measured by PIR, as well as performance across different player levels, represented by PIR across distinct quantiles, with emphasis on the 10th, 50th, and 90th quantiles. The key findings showed that "composite load" and PL·min^{-1} consistently had a positive effect on game performance overall and particularly for players at low and medium performance levels. Moreover, "composite jump load" showed significant positive effects overall and notably in players at medium performance levels. In addition, well-being was significantly associated with game performance for players at medium performance levels. In contrast, perceived recovery status did not significantly contribute to game performance. The current findings suggest that attainment of sufficient loads, possibly via extending court time as necessary, may support optimization of game performance. Moreover, sustained well-being across training and competition periods—beyond game-day measures alone—emphasizes the necessity for comprehensive daily monitoring to ensure this construct is maximized in players for optimal performance in games.

The first factor, "composite load," demonstrated a positive impact on overall game performance, particularly for players at low and medium performance levels. This suggests that players who maintain higher levels of activity during matches, as indicated by composite load, are more likely to engage in positive game actions, such as rebounds, steals, and scoring points. Previous research, particularly in the context of scoring, supports this notion as PL was significantly associated with 2-point field goals made (beta = 1.08) and points scored (beta = 1.03) during games with collegiate male basketball players.[13] Similarly, high-intensity ACC ($r = .19$), high-intensity DEC ($r = .28$), and COD to the left ($r = .24$) were partially associated with points scored during games in high school male basketball players.[44] Furthermore, explosive efforts ([IMA ACC + IMA DEC + IMA left COD + IMA right COD + IMA high-intensity jumps]/session count) were significantly related to points scored ($r = .42$) during games in collegiate female basketball players.[7] Finally, sRPE ($r = .50$) presented a significant relationship with PIR in professional male basketball players.[45] Our study provides further insights beyond the existing evidence by demonstrating that players at low and medium performance levels may rely more heavily on a composite load encompassing various metrics to enhance their game contributions. Players performing at lower levels, often substitutes or rotation players, may display increased PL and other external load metrics when given extended playing time or increased involvement by coaching staff. This exposure may enable these players to attune to game dynamics, establish rhythm, and thereby improve performance as indicated by their PIR.[5]

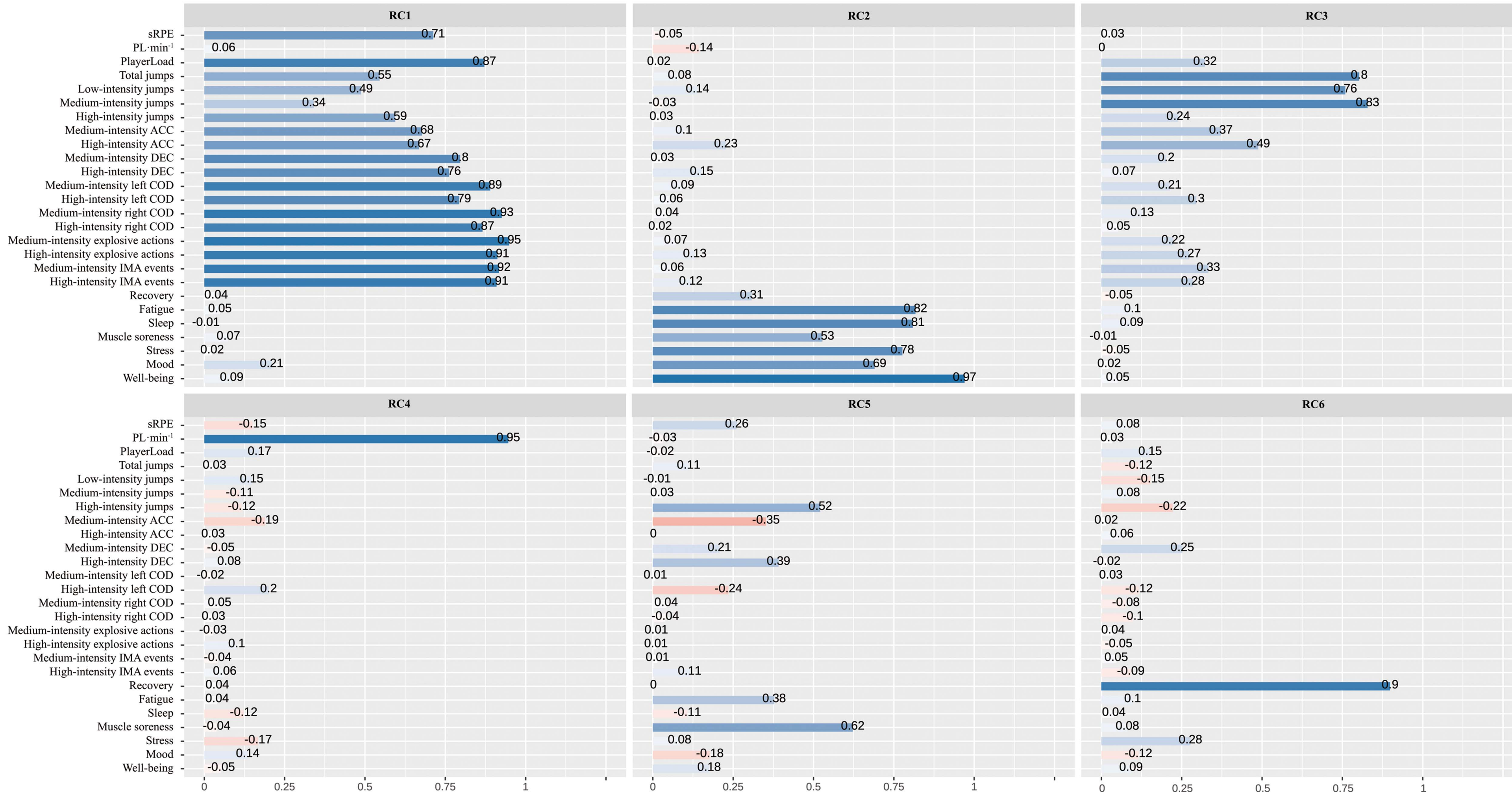

Figure 1 — RC loadings for each variable on the 6 factors using varimax rotation. ACC indicates accelerations; DEC, decelerations; COD, changes of direction; IMA, inertial movement analysis; RC, rotated component; sRPE, session rating of perceived exertion; PL, PlayerLoad.

Table 3 Quantile-Regression Coefficients for the Contribution of Extracted Factors to Game Performance (Performance Index Rating) Across Different Quantiles (10th, 50th, and 90th) Along With OLS Estimates

			Quantile		
Component	**Tau**	**OLS**	**10th**	**50th**	**90th**
RC1: composite load	Beta	0.22	0.13	0.32	0.05
	Lower	0.10	0.01	0.15	–0.29
	Upper	0.35	0.25	0.50	0.40
	P	<.001***	.044*	<.001***	.754
RC2: well-being	Beta	0.32	0.25	0.39	0.49
	Lower	–0.04	–0.06	0.18	–0.61
	Upper	0.68	0.56	0.61	1.6
	P	.086	.124	<.001***	.394
RC3: composite jump load	Beta	0.52	0.31	0.65	0.20
	Lower	0.23	–0.03	0.23	–0.26
	Upper	0.81	0.64	1.08	0.67
	P	<.001***	.075	.003**	.395
RC4: PlayerLoad per minute	Beta	1.77	1.88	1.93	1.75
	Lower	0.96	0.92	1.02	–0.33
	Upper	2.58	2.86	2.85	3.83
	P	<.001***	<.001***	<.001***	.915
RC5: muscle soreness	Beta	–0.03	0.01	0.01	0.20
	Lower	–1.3	–1.18	–1.94	–3.54
	Upper	1.24	1.18	1.94	3.95
	P	.965	.989	.985	.915
RC6: recovery	Beta	0.01	–0.93	–0.46	0.85
	Lower	–1.19	–2.06	–2.01	–2.35
	Upper	1.19	0.20	1.10	4.05
	P	.997	.110	.567	.604

Abbreviations: ACC, accelerations; COD, changes of direction; DEC, decelerations; IMA, inertial movement analysis; OLS, ordinary least squares; sRPE, session rating of perceived exertion. Note: The OLS estimates offer a baseline comparison, showing the average effect of each component across the entire distribution. Composite load includes sRPE, PlayerLoad, medium-intensity ACC, high-intensity ACC, medium-intensity DEC, high-intensity DEC, medium-intensity left COD, high-intensity left COD, medium-intensity right COD, high-intensity right COD, medium-intensity explosive actions, high-intensity explosive actions, medium-intensity IMA events, and high-intensity IMA events; composite jump load includes total jumps, low-intensity jumps, and medium-intensity jumps.
$^{*}P \le .05$; $^{**}P \le 0.01$; $^{***}P \le .001$.

PL·min^{-1} exhibited a similar trend to "composite load," showing the strongest positive impact on overall game performance, particularly among players at low and medium performance levels. This finding is consistent with previous studies, which reported significant associations between PL·min^{-1} and points scored during games ($r = .54$) in collegiate female basketball players.[7] In this way, a high PL·min^{-1} indicates a greater rate of external movement being performed, which may prove advantageous during key game scenarios, like fast breaks, defensive rotations, and gaining optimal position more efficiently.[46] Such instances would likely increase the occurrence of positive outcomes that augment the PIR statistic, such as scoring opportunities, securing rebounds, executing assists, creating steals and blocks, and drawing fouls from opponents, particularly for players at low and medium performance levels. For these players, this advantage may be especially pertinent as they likely rely on sustaining high-intensity physical engagement to compensate for reduced technical proficiency and make a meaningful contribution to team performance compared with higher-performing players.[47] In addition, "composite jump load" significantly contributed to in-game performance, especially in players at medium performance levels. This finding may be explained by the importance of vertical jumping ability in executing key actions such as rebounding, shot blocking, and scoring via jump shots or close to the basket.[38] The current evidence suggests that coaches may need to adequately consider jump conditioning stimuli within training plans, especially for medium-level players, to optimize explosive power generation in the vertical direction and ensure players can execute them consistently during game scenarios when repeated jumps are required.

In addition to external and internal load variables, perceptual well-being ratings had a significant positive effect on game performance for players performing at medium levels. This finding underscores the importance of adequate muscle soreness, sleep, mood, fatigue, and stress management in sustaining performance for the average player.[48] It is worth noting that in our study, we found no significant contribution of perceived muscle soreness (within the well-being dimensions) and recovery status on game

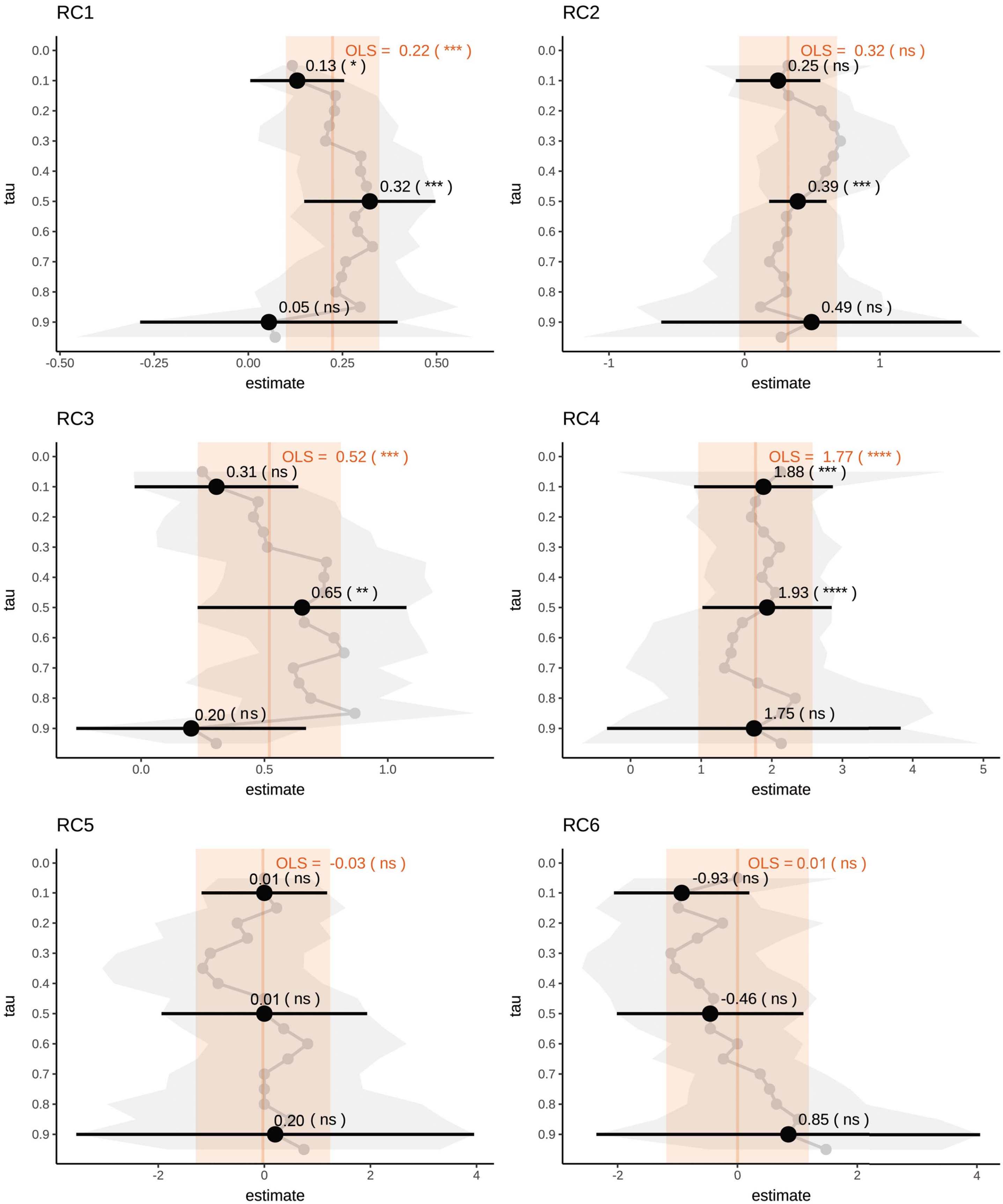

Figure 2 — Plot of quantile-regression coefficients for the contribution of extracted factors on game performance (performance index rating) across different quantiles (10th, 50th, and 90th). ACC indicates accelerations; DEC, decelerations; COD, changes of direction; IMA, inertial movement analysis; ns, not significant; OLS, ordinary least squares; RC, rotated component; RC1, composite load (including sRPE, PL, medium-intensity ACC, high-intensity ACC, medium-intensity DEC, high-intensity DEC, medium-intensity left COD, high-intensity left COD, medium-intensity right COD, high-intensity right COD, medium-intensity explosive actions, high-intensity explosive actions, medium-intensity IMA events, and high-intensity IMA events); RC2, well-being; RC3, composite jump load (including total jumps, low-intensity jumps, and medium-intensity jumps); RC4, PlayerLoad per minute; RC5, muscle soreness; RC6, recovery; sRPE, session rating of perceived exertion. $^{*}P \le .05$; $^{**}P \le .01$; $^{***}P \le .001$.

performance overall and for players performing at different levels. This finding is somewhat surprising given the common assumption that well-managed muscle soreness and optimal recovery status are crucial for optimal player readiness and performance.[8] The discrepancy between our findings and these assumptions can be explained by 2 factors. First, muscle soreness reflects only one dimension of overall well-being and may exert limited influence when assessed in isolation.[49] However, its impact becomes more pronounced when evaluated alongside other wellness dimensions, as demonstrated by the significant effects of overall well-being observed in this study. Second, the 6 to 20 scale used to assess recovery status may lack the sensitivity to capture subtle variations within players. Future research could benefit from employing more granular scales with higher resolution. For instance, studies have shown that RPE scales ranging from 1 to 100 are more effective in detecting variations in intensity than those ranging from 1 to 10.[50] A similar trend may apply to the perceptual recovery scales utilized in this study, as suggested in the literature.[50]

A major strength of this study involves the use of QR, which allowed us to capture nuanced relationships between external and internal loads, perceived recovery status, and well-being with PIR across various levels of player performance. Whereas OLS regression estimates average effects across the entire data set, QR offers deeper insights into how the investigated factors influence player performance at distinct points across the PIR distribution.[38] For example, well-being showed no significant effect in the OLS analysis but had a significant positive effect at the 50th quantile. This finding underscores the importance of well-being for players performing at a medium level—an insight that traditional regression methods would have overlooked. Uncovering these differences makes QR a powerful tool in sports performance analysis, particularly in basketball, where the influence of various factors can vary widely among players at different performance levels.

Despite these strengths, this study has important limitations that should be acknowledged. First, the analysis did not account for contextual variables, such as game location, opponent strength, and scoring line, which can significantly influence player performance.[51,52] Including these variables in future studies could provide a more comprehensive understanding of factors that impact PIR within specific game contexts and scenarios. Second, a potential limitation of this study is the lack of reported reliability or validity data for the online questionnaire used to assess player well-being. Although the questionnaire was adapted specifically for basketball players, the absence of validation may limit the accuracy and generalizability of the findings. Future research should consider using well-being scales with established reliability and validity metrics or undertake validation studies for this adapted questionnaire to strengthen the robustness of the well-being assessments. Third, a notable limitation of this study is the relatively small sample size, which may constrain statistical power, particularly in dimension-reduction analyses. Although this sample size is typical within the context of professional sports research, a larger cohort would likely improve the generalizability of the principal component structure. Future studies are encouraged to incorporate bootstrap validation techniques to further assess the stability and robustness of the findings, thereby enhancing the reliability and generalizability.

Practical Applications

This study highlights the importance in optimizing player loading in games, particularly considering the "composite load" factor analyzed and $PL \cdot min^{-1}$, as well as in players performing at low and medium levels. In this way, optimizing tactical strategies to allow lower-performing and medium-performing players to accrue sufficient loading via exposure to gameplay may allow them to better adapt to the rhythm and demands of competition, which may contribute to a higher PIR as their load increases. Consequently, to achieve this goal, particular attention should be given to developing players' work rate capacities, enabling them to sustain higher average external intensities ($PL \cdot min^{-1}$) and, thereby, effectively improve their PIR. Furthermore, the impact of the "composite jump load" metric analyzed on player performance emphasizes the importance of targeted training to improve the magnitude and ability to repeatedly express vertical power for key game actions that contribute to positive performance outcomes, such as rebounding, shooting, and shot blocking. Coaches should integrate jump training into tactical drills, focusing not only on physical development but also on the strategic application of jumping skills within team play.

The significant role of well-being among players performing at medium levels suggests that regular wellness monitoring, combined with strategies to optimize sleep, mood, stress, fatigue, and soreness, may be particularly important for in-game performance throughout the season. Indeed, such strategies are likely to be most effective when implemented at an individualized level given that we showed that the impact of well-being varies among players at different performance levels. Given the limited influence of perceived recovery on performance, combining subjective perceptual measures with objective measures could provide a more comprehensive understanding of player recovery needs. Holistically, our results lend support for a balanced approach to wellness management and physical training to optimize in-game basketball performance for players within the team performing at various levels.

Conclusions

This study provides valuable insights into the complex relationships between game load, perceived recovery status, and well-being with in-game basketball performance across players at different performance levels. Our findings demonstrate that composite load, encompassing various external- and internal-load variables, and PlayerLoad per minute were significantly and positively related to performance, particularly for players at low and medium performance levels. These outcomes highlight the importance of effective load management and neuromuscular conditioning among players within teams. The significant, positive association between well-being and performance for players at medium levels further emphasizes the need for targeted interventions aimed at optimizing player mood, sleep, stress, soreness, and fatigue levels. The nonsignificant effects of perceived recovery suggest that this metric may be less impactful to performance in the sample of players investigated.

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