

# Are acute player workloads associated with in-game performance in basketball?

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**ABSTRACT:** To investigate associations between acute workload and in-game performance in basketball. Eight semi-professional, male basketball players were monitored during all training sessions (N = 28) and games (N = 18) across the season. External workload was determined using absolute (arbitrary units[AU]) and relative (AU·min<sup>-1</sup>) PlayerLoad™ (PL), and absolute (count) and relative (count·min<sup>-1</sup>) low-intensity, medium-intensity, high-intensity, and total Inertial Movement Analysis (IMA) events (accelerations, decelerations, changes-of-direction, and jumps). Internal workload was determined using absolute and relative Summated-Heart-Rate-Zones workload, session-rating of perceived exertion, rating of perceived exertion, and time (min) spent working > 90% of maximal heart rate. In-game performance was indicated by the player efficiency statistic. Repeated measures correlations were used to determine associations between acute workload variables (across the previous 7 days) and player efficiency. Relative PL (r = 0.13, small) and high-intensity IMA events (r = 0.13, small) possessed the strongest associations with player efficiency of the investigated workload variables (P > 0.05). All other associations were trivial in magnitude (P > 0.05). Given the trivial-small associations between all external and internal workload variables and player efficiency, basketball practitioners should not rely solely on monitoring acute workloads to determine performance potential in players.

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## INTRODUCTION

In basketball, successful performance during competition is influenced by the appropriateness of the training stimuli prescribed across various seasonal phases. Specifically, training is prescribed to promote favorable physical and physiological adaptations [1] and to subsequently align peak performance with competition [2]. For training to be precisely administered and modified where necessary across the annual plan, player workloads must be accurately quantified [1]. Workload can be categorized as either external or internal [3]. External workload represents the volume or intensity of the training and competition stimuli imposed, while internal workload refers to the physiological and perceptual demands that occur in response to training and competition [3].

In basketball, external workload is most frequently assessed via microsensor-based monitoring systems due to their underlying practical advantages [4]. Specifically, data collection using microsensors is simple and non-invasive for players, while proprietary software permits efficient data processing to inform athlete management and training prescription in a timely manner [1, 4]. When utilizing

microsensor data however, proprietary software typically generates many objective measures which can create difficulties for basketball practitioners in selecting the most suitable variables to report in practical settings. Furthermore, a combination of objective (e.g. microsensor-derived metrics and heart rate) and subjective (e.g. rating of perceived exertion) variables has been advocated for player monitoring in team sports [5] as they offer different information regarding the demands of training and competition. Consequently, basketball practitioners are often presented with an abundance of potential variables to interpret simultaneously when quantifying and subsequently manipulating the volume and intensity completed by players.

In addition to the wide selection of available variables presented to basketball practitioners when monitoring players, another practical issue that arises concerns the multi-faceted application of workload data. Specifically, player monitoring can be implemented to quantify and adjust the volume and intensity imposed on players to optimize various aspects of interest including anaerobic and aerobic performance,

fatigue, and injury symptoms [6]. In turn, promoting positive adaptations will mitigate the likelihood of maladaptive training responses and may in turn lead to favorable performance outcomes [6]. While there has been some investigation into the association between workload and performance in team sports [7, 8], data examining this relationship in basketball are limited [9, 10, 11]. More precisely, Caparros *et al.* [9] examined the relationships between exposure (frequency and duration of training sessions and games completed) and game-related statistics across a season in professional, male basketball players. There were significant ( $P < 0.05$ ) correlations between exposure and mean points scored in players ( $r = 0.77$ ) as well as team ranking ( $r = 0.76$ – $0.87$ ). However, one limitation of using only exposure to quantify training and game demands is that it does not effectively capture the stimulus imposed given it is essentially a measure of training and playing frequency or duration [6]. In another study, Cruz *et al.* [10] examined the relationships between session-rating of perceived exertion (sRPE) and changes in counter-movement jump height following 9 weeks of in-season training and competition in young, elite, female basketball players. There was a significant, small inverse correlation between sRPE and counter-movement jump height ( $r = -0.28$ ,  $P < 0.05$ ) [10]. While the evidence provided by Cruz *et al.* [10] is interesting, the utilization of a single, subjective volume measure and a single performance measure not representative of actual game situations (counter-movement jump height) limits the application of findings specifically to in-game performance. Lastly, Vazquez-Guerrero *et al.* [11] assessed whether players who performed higher acute (7-day) and chronic (28-day) activity volumes prior to competition performed better, as measured via game-related statistics (Winscore, Performance Index Rating, and Player Total Contribution). It was revealed that when players were grouped based on in-game performance, better performing players did not complete higher activity volumes [11]. While this information is practically important, it only gives insight regarding whether higher activity volumes are inductive to better performance but does not assess whether the volume of activity completed by players relates to performance-based outcomes. Identifying whether associations exist between workload and performance is important for basketball practitioners to guide their choice of workload variables for use in practice. Consequently, more detailed investigations in basketball are warranted to determine the association between workload and in-game performance using a wider range of variables.

Given training is prescribed to promote favorable performance during competition [2], identifying volume or intensity measures which are most strongly associated with practical indicators of in-game performance is of high priority to basketball practitioners. When attempting to anticipate performance-related outcomes, workloads are typically quantified over acute (7 days) and chronic (28 days) periods [12, 13]. However, acute workloads are readily planned and adjusted by basketball practitioners according to the game schedule faced and therefore likely fluctuate more readily than chronic workloads across the season in basketball teams [14]. Consequently,

to comprehensively investigate the relationship between in-season workload and performance in basketball, the present study aimed to determine whether acute external and internal workloads are associated with in-game performance in basketball.

## MATERIALS AND METHODS

An observational study design was utilized whereby players were monitored during the in-season phase of an entire competitive season. The 6-week pre-season phase was used as a familiarization period for players to become accustomed to monitoring procedures with pre-season data not included in final analyses. Players were monitored during all training sessions and games during the 15-week in-season phase. Players completed 1–3 training sessions per week with games held between Friday and Sunday at home and away venues. Across the season,  $33 \pm 8$  (range = 17–42) observations per player were obtained. All games consisted of 4 x 10-min quarters. During the season, 18 games were played including 2 double-headers (2 games played on consecutive nights), 1 triple-header (3 games played on consecutive nights or days), and 11 single-game weeks.

Eight semi-professional, male basketball players (age:  $23 \pm 4$  yr; stature:  $191 \pm 8$  cm; body mass:  $87 \pm 16$  kg; semi-professional playing experience:  $5 \pm 2$  yr) volunteered to participate in the study. Players from the same team who only attended training or were expected to receive limited playing time across the season were not routinely monitored and therefore could not be considered for inclusion in this study. All players were registered in the Queensland Basketball League, which is a second-tier, state-level Australian basketball competition. Prior to study commencement, players were screened for any injuries or health conditions that prevented safe participation in the study. All players were over 18 years of age and provided written informed consent prior to participation. All procedures were approved by the Central Queensland University institutional Human Research Ethics Committee.

Prior to each training session and game, players were fitted with upper-body garments containing microsensors held between the scapulae (OptimEye s5, Catapult Innovations, Melbourne, Australia) and chest-worn heart rate (HR) monitors (Polar T31, Polar Electro, Kempele, Finland) worn under their regular attire. At the first pre-season training session, anthropometric data were collected for each player including stature using a portable stadiometer (Seca 213, Seca GMBH, Hamburg, Germany) and body mass using electronic scales (BWB-600, Tanita Corporation, Tokyo, Japan). Across the monitoring period, all training sessions were prescribed by coaching staff. Training sessions primarily consisted of games-based training designed to develop tactical and technical aspects with the application of fitness components. Games-based training also varied through manipulation of player numbers, substitution strategies, and court size. Consistent with previous work, all data analyses excluded warm-up activities (*i.e.* jogging, dynamic stretching, and repeated sprints) and included all rest periods across training (*e.g.* breaks between drills) and games (*e.g.* inter-quarter breaks and substitutions) [2].

Microsensor and HR data were recorded continuously across all training sessions and games and downloaded following each session to a personal computer for analysis using proprietary software (Open-Field Version 1.17, Catapult Innovations, Melbourne, Australia). HR data were exported in 1-s epochs and subsequently analyzed in Microsoft Excel (Version 15.0; Microsoft Corporation; Redmond, WA, USA). Following each training session and game, players gave their rating of perceived exertion (RPE) using Borg's Category Ratio Scale (CR10) [15]. RPE was collected within 30 minutes of completing each training session or game [16] away from other players to avoid any peer influence during reporting.

External workload was derived from the accelerometer component of the microsensor and reported as absolute (arbitrary units [AU]) and relative (AU·min<sup>-1</sup>) PlayerLoad™ (PL) to represent volume and intensity, respectively. PlayerLoad™ is the proprietary accumulated load measure calculated as the square root of the sum of the squared rate of change in acceleration across the transverse (x), coronal (y),

and sagittal (z) planes multiplied by a scaling factor of 0.01 using the following formula [17]:

$$[\sqrt{(a_{y1} - a_{y-1})^2 + (a_{x1} - a_{x-1})^2 + (a_{z1} - a_{z-1})^2}] * 0.01$$

In addition, inertial movement analysis (IMA) variables were recorded. IMA variables are proprietary metrics of the microsensor based on the direction traveled by each player, subsequently categorized as the number of accelerations (-45° to 45°) decelerations (-135° to 135°), and changes-of-direction (COD; -135° to -45° for left COD and 45° to 135° for right COD) in total and at low (1.5–2.5 m·s<sup>-2</sup>), medium (2.5–3.5 m·s<sup>-2</sup>), and high (> 3.5 m·s<sup>-2</sup>) intensities. Jumps were also detected using proprietary algorithms and reported as a total count as well as the number of low- (0–20 cm), medium- (20–40 cm), and high-intensity (> 40 cm) jumps. All IMA events were also tabulated by summing the number of accelerations, decelerations, COD, and jumps and reported in total as well

**TABLE 1.** Acute external and internal workload variables and player efficiency across the in-season phase in semi-professional, male basketball players.

Outcome measure	Mean ± SD
<b>External workload volume</b>	
PlayerLoad™ (AU)	1157 ± 521
Low-intensity IMA events (count)	922 ± 380
Medium-intensity IMA events (count)	278 ± 121
High-intensity IMA events (count)	125 ± 65
Total IMA events (count)	1325 ± 556
<b>External workload intensity</b>	
PlayerLoad™ (count·min <sup>-1</sup> )	5.7 ± 1.1
Low-intensity IMA events (count·min <sup>-1</sup> )	4.6 ± 0.9
Medium-intensity IMA events (count·min <sup>-1</sup> )	1.4 ± 0.3
High-intensity IMA events (count·min <sup>-1</sup> )	0.6 ± 0.2
Total IMA events (count·min <sup>-1</sup> )	6.7 ± 1.4
<b>Objective internal workload</b>	
Summated-Heart-Rate-Zones (AU)	445 ± 185
Summated-Heart-Rate-Zones (AU·min <sup>-1</sup> )	2.3 ± 0.8
Time spent > 90% HR <sub>max</sub> (min)	4.5 5.5
<b>Subjective internal workload</b>	
Session-rating of perceived exertion (AU)	1211 ± 554
Rating of perceived exertion (AU)	6.0 ± 1.3
<b>In-game performance</b>	
Player efficiency (AU)	14.9 ± 11.8

Note: SD = standard deviation; AU = arbitrary units; IMA = inertial movement analysis; acute workload determined across the 7-day period prior to each game.

**TABLE 2.** Results of the repeated measures correlations between acute workload measures and in-game performance (player efficiency) in semi-professional, male basketball players.

Workload variable	r	95% CI	P
<i>External workload</i>			
PlayerLoad	0.022	-0.182, 0.225	0.832
PlayerLoad·min <sup>-1</sup>	0.131	-0.075, 0.326	0.206
Low-intensity IMA events	-0.075	-0.275, 0.130	0.468
Low-intensity IMA events·min <sup>-1</sup>	-0.055	-0.256, 0.150	0.594
Medium-intensity IMA events	-0.025	-0.228, 0.179	0.808
Medium-intensity IMA events·min <sup>-1</sup>	0.083	-0.123, 0.282	0.423
High-intensity IMA events	0.009	-0.195, 0.213	0.928
High-intensity IMA events·min <sup>-1</sup>	0.129	-0.077, 0.324	0.213
Total IMA events	-0.057	-0.258, 0.148	0.581
IMA events·min <sup>-1</sup>	-0.004	-0.207, 0.200	0.972
<i>Internal workload</i>			
Session-RPE	-0.040	-0.242, 0.165	0.698
RPE	-0.082	-0.281, 0.124	0.428
SHRZ	-0.013	-0.217, 0.191	0.897
SHRZ·min <sup>-1</sup>	0.020	-0.185, 0.223	0.849
Time spent > 90% HR <sub>max</sub>	-0.011	-0.214, 0.193	0.917

Note: CI = confidence interval; IMA = inertial movement analysis; RPE = rating of perceived exertion; SHRZ = Summated-Heart-Rate-Zones.

as according to intensity (low, medium, and high). The reliability of PL (coefficient of variation [CV] = 4.6–13.1%) [18] and IMA (CV = 3.1–6.7%) [19] variables have been previously reported in team sport athletes.

Internal workload was objectively measured using a modified Summated-Heart-Rate-Zones (SHRZ) [20] model as well as the time (min) spent > 90% of individualized maximal heart rate ( $HR_{max}$ ) given time > 90%  $HR_{max}$  has consistently shown strong associations with performance in team sports [6]. To determine SHRZ, time (min) spent in predefined HR zones was calculated, with each zone spanning 2.5% of each player's  $HR_{max}$  between 50–100% and multiplied by corresponding weightings of 1–5.75 (e.g. zone 1 = 50–52.49%  $HR_{max}$ , zone 2 = 52.50–54.9%  $HR_{max}$ ). Workload was subsequently determined as the sum of the accumulated weightings in each zone [20].  $HR_{max}$  was determined as the highest HR recorded during a training session or game [21]. In addition, session-rating of perceived exertion (sRPE) and RPE were determined to indicate perceptual volume and intensity, respectively. sRPE was determined by multiplying individualized RPE by the duration of the session or game (min). All workload data are quantified as the weekly volume (sum of all workload accumulated in the 7 days prior to each game) and average intensity (volume divided by duration [ $\cdot \text{min}^{-1}$ ]).

In-game performance was determined using the individual player efficiency statistic. Player efficiency is an individualized measure of in-game performance that combines positive and negative components to determine contribution to a game using the following formula: Player efficiency = (points + rebounds + assists + steals + blocks) – (missed field goals + missed free-throws + turnovers). Individual game-related statistics used to calculate efficiency for each player were officially recorded by qualified personnel and freely available online (sportsg.com) following each game. Game-related statistics were imported into a Microsoft Excel spreadsheet (Version 15.0; Microsoft Corporation; Redmond, WA, USA) for further calculations.

All data are reported as mean  $\pm$  standard deviation (SD). To determine the associations between workload and performance, separate repeated-measures correlations ( $r$ ) with 95% confidence intervals (CI) were calculated using Fisher's transformation to account for multiple observations collected on each player [22, 23]. Correlation magnitudes were interpreted as: *trivial* = < 0.10, *small* = 0.10–0.29, *moderate* = 0.30–0.49, *large* = 0.50–0.69, *very large* = 0.70–0.89, and *nearly perfect* = 0.90–1.00 [24]. Significance was accepted where  $P < 0.05$ . All analyses were conducted using Stata/MP 16.0 for Windows (StataCorp LLC, College Station, TX, USA).

## RESULTS

Weekly workloads and player efficiency are presented in Table 1, with the repeated-measures correlation coefficients presented in Table 2. PL  $\cdot \text{min}^{-1}$  and high-intensity IMA events  $\cdot \text{min}^{-1}$  revealed *small*, positive associations with player efficiency ( $r = 0.13$ ,  $P = 0.21$ ). All other associations between workload measures and player efficiency were *trivial* in magnitude ( $r = -0.08$  to  $0.08$ ,  $P > 0.05$ ).

## DISCUSSION

To our knowledge, the present study represents the most comprehensive investigation of the association between workload and in-game performance in basketball to date. Average intensity (PL  $\cdot \text{min}^{-1}$ ) and relative high-intensity activity (IMA events  $\cdot \text{min}^{-1}$ ) encountered by players the week preceding competition revealed *small*, positive associations with in-game performance (player efficiency). These findings are similar to those reported in previous work [11], revealing the limited sensitivity of external volume and intensity variables to distinguish between high- and low- performing players. Therefore, given only *small* associations were apparent, our data suggest acute workloads should not be solely relied upon to understand in-game performance potential in players.

While some external variables possessed *small* associations with player efficiency during games, all internal volume and intensity variables possessed *trivial* associations with player efficiency. The lack of a relationship between internal variables and in-game performance might be expected considering the acute timeframes examined. Specifically, given internal workload governs the responses of players and subsequent physiological adaptations to training, it is the internal workload that will ultimately dictate performance-related outcomes [25]. The present study considered acute (7 days) workloads and therefore, it is likely that this timeframe was not sufficient to induce any noticeable improvements in physiological outcomes (e.g. fitness changes) in the trained players we monitored. In addition, these data were sampled during the in-season phase so it can be expected that fitness was higher than during the pre-season phase, where the focus is typically on improving capacities leading into the competitive season [26]. While team sport research has consistently shown positive associations between HR and performance [6], performance has typically been operationalized as changes in fitness variables, either across multiple weeks or an entire seasonal phase [6]. As such, it is expected that where activity demands evoke higher HR responses in players, positive adaptations would be reflected in changes in fitness parameters but may not necessarily translate into significant improvements in in-game performance indicated as player efficiency [6].

Considering the subjective data obtained (sRPE), our data revealed non-significant, *trivial* associations with in-game performance. However, sRPE may give different insight regarding player preparation leading into games than objective internal measures such as HR variables given it is more strongly influenced by psychological and cognitive demands [27]. For example, sRPE has been consistently associated with markers of athlete well-being during intensified training periods [27]. Therefore, subjective measures of internal workload, while not correlated with player efficiency in this study, should not be considered as unimportant as they may be able to detect signs of maladaptive responses [27]. Furthermore, the present study utilized the conventional CR10 scale as this is the only method of reporting RPE validated in basketball [28]. In other team sports however, the use of a 0–100 RPE scale [29] and differential exertion scales related to specific responses (e.g. respiratory and muscular) [30] have

been shown to strengthen associations between sRPE and performance-related outcomes compared to the traditional scale. As such, investigating the potential applications of these RPE scales to calculate sRPE when monitoring players in basketball warrants further investigation.

While the present study provides important insights regarding the association between workload and performance in basketball, there are limitations that should be considered. First, data were collected on a single, semi-professional, male basketball team and therefore our findings should not be generalized to other levels of competition [31] or to female players. Second, while the present study revealed *small*, positive associations between selected external workload variables and in-game performance, these findings should be used to guide the choice of variables utilized in practice rather than dictate the precise workload targets to be prescribed. Specifically, manipulating activity volume and intensities for players must still be guided by effective training prescription principles (e.g. overloading and tapering) and manipulated based on the individual needs of players and teams. Third, this study focused on acute timeframes and only adopted a single in-game performance measure to give a global indicator of

in-game performance. Nevertheless, different findings may result from other timeframes and indicators of in-game performance.

### CONCLUSIONS

Given only *small* associations between  $\text{PL}\cdot\text{min}^{-1}$  and high-intensity IMA events $\cdot\text{min}$  with in-game performance were revealed, these data should not be used in isolation when seeking to optimize the performance potential of players. Acute internal workload variables showed *trivial* associations with in-game performance suggesting that reliance on weekly internal workloads involving HR- and RPE-based measures to indicate performance potential may not be advisable in basketball players.

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### Conflict of interest declaration

All authors declare they have no conflicts of interest.

### REFERENCES

1. Fox J, Scanlan A, Stanton R. A review of player monitoring approaches in basketball: Current trends and future directions. *J Strength Cond Res.* 2017; 31(7):2021–2029.
2. Fox L, Stanton R, Scanlan A. A comparison of training and competition demands in semiprofessional male basketball players. *Res Q Exerc Sport.* 2018;89(1):103–111.
3. McLaren S, MacPherson T, Coutts A, Hurst C, Spears I, Weston M. The relationships between internal and external measures of training load and intensity in team sports: A meta-analysis. *Sports Med.* 2017;48(3):641–658.
4. Fox J, Scanlan A, Sargent C, Stanton R. A survey of player monitoring approaches and microsensor use in basketball. *J Hum Sport Exerc.* 2020;15(1).
5. Bourdon P, Cardinale M, Murray A, Gastin P, Kellmann M, Varley M, Gabbett T, Coutts A, Burgess D, Gregson, W, Cable T. Monitoring athlete training loads: Consensus statement. *Int J Sports Physiol Perform.* 2017; 12(S2):S2-161-S2-170.
6. Fox J, Stanton R, Sargent C, Wintour S, Scanlan A. The association between training load and performance in team sports: A systematic review. *Sports Med.* 2018;48(12):2743–2774.
7. Fitzpatrick J, Hicks K, Hayes P. Dose-response relationship between training load and changes in aerobic fitness in professional youth soccer players. *Int J Sports Physiol Perform.* 2018;13(10):1365–1367.
8. McCaskie C, Young W, Fahrner B, Sim M. Association between pre-season training and performance in elite Australian football. *Int J Sports Physiol Perform.* 2018;14(1):68–75.
9. Caparrós T, Alentorn-Geli E, Myer G, Capdevila L, Samuelsson K, Hamilton B, Rodas G. The relationship of practice exposure and injury rate on game performance and season success in professional male basketball. *J Sports Sci Med.* 2016;15(3):397–402.
10. Cruz I, Pereira L, Kobal R, Kitamura K, Cedra C, Loturco I, Cal Abad C. Perceived training load and jumping responses following nine weeks of a competitive period in young female basketball players. *PeerJ.* 2018;6.
11. Vázquez-Guerrero J, Casals M, Corral-López J, Sampaio J. Higher training workloads do not correspond to the best performances of elite basketball players. *Res Sports Med.* 2020; 28(4):540–552.
12. Murray N, Gabbett T, Townshend A, Blanch P. Calculating acute: chronic workload ratios using exponentially weighted moving averages provides a more sensitive indicator of injury likelihood than rolling averages. *Br J Sports Med.* 2017; 51(9):749–754.
13. Murray N, Gabbett T, Townshend A, Hulin B, McLellan C. Individual and combined effects of acute and chronic running loads on injury risk in elite Australian footballers. *Scan J Med Sci Sports.* 2016;27(9):990–998.
14. Conte D, Kolb N, Scanlan A, Santolamazza F. Monitoring training load and wellbeing during the in-season phase in National Collegiate Athletic Association Division 1 men's basketball. *Int J Sports Physiol Perform.* 2018; 13:1067–1074.
15. Borg G, Hassmen P, Lagerstrom M. Perceived exertion related to heart rate and blood lactate during arm and leg exercise. *Eur J App Physiol Occ Physiol.* 1987;56:679–685.
16. Fanchini M, Ghielmetti R, Coutts A, Schena F, Impellizzeri F. Effect of training-session intensity distribution on session rating of perceived exertion in soccer players. *Int J Sports Physiol Perform.* 2015;10:426–430.
17. Boyd L, Ball K, Aughey R. The reliability of MinimaxX accelerometers for measuring physical activity in Australian football. *Int J Sports Physiol Perform.* 2011;6:311–321.
18. Barrett S, Midgley A, Lovell R. PlayerLoad™: Reliability, convergent validity, and influence of unit positioning during treadmill running. *Int J Sports Physiol Perform.* 2014;9:945–952.
19. Luteberget L, Holme B, Spencer M. Reliability of wearable measurement units to measure physical activity in team handball. *Int J Sports Physiol Perform.* 2017;13(4):467–473.
20. Scanlan A, Fox J, Poole J, Conte D, Milanovic Z, Lastella M, Dalbo V. A comparison of traditional and modified Summated-Heart-Rate-Zones models to measure internal training load in

- basketball players. *Meas Phys Educ Exerc Sci.* 2018;22(4):303–309.
21. Berkelmans D, Dalbo V, Fox J, Stanton R, Kean C, Giamarelos K, Teramoto M, Scanlan A. Influence of different methods to determine maximum heart rate on training load outcomes in basketball players. *J Strength Cond Res.* 2018; 32(11):3177–3185.
  22. Bakdash J, Marusich L. Repeated Measures Correlation. *Front Psychol* 2017;8.
  23. Bland J, Altman D. Calculating correlation coefficients with repeated observations: Part 2—Correlation between subjects. *Br Med J.* 1995;310.
  24. Hopkins W. A scale of magnitudes for effect statistics. Available from: <http://www.sportsci.org/resource/stats/index.html>. Accessed 3 January, 2020
  25. Akubat I, Barrett S, Abt G. Integrating the internal and external training loads in soccer. *Int J Sports Physiol Perform.* 2014;9(3):457–462.
  26. Kelly V, Coutts A. Planning and monitoring training loads during the competition phase in team sports. *Strength Cond J.* 2007;29(4):32–37.
  27. Saw A, Main L, Gastin P. Monitoring the athlete training response: Subjective self-reported measures trump commonly used objective measures: A systematic review. *Br J Sports Med.* 2016; 50(5):281–291.
  28. Manzi V, D'Ottavio S, Impellizzeri F, Chaouachi A, Chamari K, Castagna C. Profile of weekly training load in elite male professional basketball players. *J Strength Cond Res.* 2010; 24(5):1399–1406.
  29. Coyne J, Haff G, Coutts A, Newton R, Nimphius S. The current state of subjective training load monitoring: A practical perspective and call to action. *Sports Med Open.* 2018;4.
  30. Weston M, Siegler J, Bahnert A, McBrien J, Lovell R. The application of differential ratings of perceived exertion to Australian Football League matches. *J Science Med Sport.* 2015; 18(6):704–708.
  31. Scanlan A, Dascombe B, Reaburn P. A comparison of the activity demands of elite and sub-elite Australian men's basketball competition. *J Sports Sci.* 2011;29(11):1153–1160.