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Revisiting the Acute: Chronic Workload Ratio in Basketball Using a Machine Learning Approach

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Abstract

Being able to quantify workloads has become an important part of sport in periodization, recovery, and injury risk. Within sports science, using advanced mathematical approaches has the potential to uncover deep patterns since they are not traditionally used within sport. Specifically, within professional basketball, the 82-game season, game density, and travel schedule make it important for practitioners to quantify workload to optimize player health and wellness. One common method used to calculate workload (ACWR) is the acute: chronic workload ratio which is the quotient between a weekly load (7 days) and the average monthly load (28 days). While the science behind this method is sound, there are some drawbacks that make applying it to professional basketball difficult. For example, the original ACWR was based on cricket and later rugby, which are sports with predictable game frequencies and weekly matches. Since this is untrue in the National Basketball Association (NBA), the authors explored a machine learning method in workload ratios. The purpose of this article was to use a mathematical approach paired with practitioners to help find more optimal quotients of workload within professional basketball.

Keywords: Basketball, NBA, Machine Learning, Workload

Introduction

The world of high-level sport has been transformed with the supplementation of sports science (Balagué et al., 2017). Sports science is a young field that lies at the center of statistics, data science, and strength and conditioning. As such, technology plays a key role in the data collection and monitoring process. Within the last 15 years, the field of strength and conditioning through tools like force plates and global positioning systems (GPS)/local positioning systems (LPS) and sports medicine through tools like isokinetic and isometrics testing have given rise to various breakthroughs within sports science (Beckham et al., 2014). It is now more common practice in Division 1 Programs and Professional sport for teams to have a plethora of tools to measure both internal and external workload. Much of the research on external workload was sparked by Hulin et al. (2014) (Hulin et al., 2014). This research article followed fast bowlers within Cricket and found that injury-risk was increased the week after a large training or game stimulus, rather than in the immediate days after. This approach to looking at injury risk gave rise to the acute: chronic workload ratio (ACWR) which uses 28-day cumulative load divided by a 7-day acute load to find a ratio (Hulin et al., 2016). This ratio can then inform practitioners into how to better handle players between games, weight room activities, and recovery. While this approach may work well for other sports, it may not fit the National Basketball

Association (NBA) in the United States (Esteves et al., 2021). The purpose of this paper was to form the theoretical and applicable foundations for alternate and more appropriate version of the ACWR to professional basketball.

The Evolution of Sports Science

The field of sports science is still in its infancy and has been created out of the necessity to leverage biometric data to on-court performance(West et al., 2021). Using basketball as the primary example for this paper, statistics and analytics have been around since the inception of the game. At the entry-level lies overall score of winning team vs losing team. From here, scores can be broken down within quarter and by individual player. Recently, within the last 20 years analytics have become much deeper with numbers being used to track defense, offense, player rotations, etc. (Hamdad et al., 2018). This framework and push towards leveraging data has also positively affected performance on and off the court. For example, sports technology has evolved and continues to evolve in the space of rehab, return to play, and workload monitoring. Within sports medicine, isokinetic testing has become the gold standard for return to play testing (Rivera-Brown et al., 2022). However, isokinetic machines may be expensive and have an expansive footprint making them less than ideal in the practical setting. In sports performance (strength and conditioning), data used to only be available for collection in biomechanics labs via marker systems motion capture and in-ground force plates. Once again, this technology is expensive making the entry into acquisition difficult. This has changed immensely however, with technology that has made capturing biometric and workload data more feasible and overall, more user friendly which has enabled organizations to begin incorporating sports scientists into their existing high-performance model (Kos et al., 2018).

External and Internal Workload

The concept of workload stems from wanting to leverage the aforementioned technology into actionable insights (Drew et al., 2016). Overall, workload and its tracking can be split into external and internal variables. External workload is the amount of stress and how much work the body does (Gómez-Carmona et al., 2020). Internal workload is the physiological response to the external work (McLaren et al., 2017). Some common ways to assess external workload are through tools like force plates, isometric testing, and global positioning systems (GPS)/ local positioning systems (LPS). Internal workload is more difficult to measure and currently includes heart rate variability (HRV) or certain hormonal levels like cortisol (Seshadri et al., 2019). Within the sport of basketball, organizations have the option of combining both methods to better assess overall athlete health and well-being. For example, the author's organization uses a combination of force plates, LPS, HRV to monitor athlete health and well-being.

Practical Applications to Basketball

In the NBA, the regular season consists of 82 games (41 home, 41 away) with an average of 3.5 games per week (Teramoto & Cross, 2010). This schedule makes it difficult to maintain optimal levels of objective and subjective recovery. Since physical fatigue is an encompassing and general term, fatigue in basketball can be viewed as a decrease in the aforementioned variables of performance (Edwards et al., 2018). Within force plates, this may result in decreases to RSI-modified or jump height (Jiang et al., 2021). In isometric testing, force production may decrease either maximally (Max Force) or at certain time constraints (150ms, 200ms). Within the framework of LPS systems, it has the ability to measure variables such as total distance, player loads, and amount of sprints (Altundag et al., 2022). Internally, using heart rate monitors allow for heart rate variability, sleep scores, and monitoring of heart rate zones (1-5) during training sessions (Achten & Jeukendrup, 2003). As this technology evolves, the sport scientist faces the dilemma of deciding which tools are both feasible, efficient, and least invasive to monitor athletes. Once data has been collected, the next question becomes how can this data best be utilized?

The Acute: Chronic Workload Ratio in Basketball

The basis of the ACWR began as a method to monitor athlete workloads and injury risk over time which may occur from delayed training effects (Impellizzeri et al., 2020). For example, within strength and conditioning it is known that training effects (positive and negative) do not occur instantaneously. In resistance training programs, the first adaptations are neural and generally occur within 4 weeks (motor unit recruitment, increased firing rate) while structural changes (muscle cross-sectional area, hypertrophy) take from >6+ weeks to occur (Sale, 1988). Extrapolating this line of thinking, injury does not typically occur right after a spike or acute increase in athletic workload. It may take days, weeks, and sometimes months for the detriments of increased workloads to disturb athletic homeostasis enough to cause injury. Thus, Hulin et al. (2014) proposed the ACWR as a means of predicting injury risk (Hulin et al., 2014). The ratio is calculated by taking the average workload over a 7-day period (acute) and dividing it by the average of a 28-day period (chronic). The original study was performed on cricket players and this model has been applied successfully in other sports such as rugby, aussie rules football, and soccer. Calvert et al. (1976) were among the first to quantify the relationship between fitness and fatigue through time constraints (Calvert et al., 1976). One reason injury risk can be quantified and predicted to a sense in these sports is their established frequency of play in the regular season. Each of the aforementioned sports play games/matches 1-2 times per week (Bowen et al., n.d.). Furthermore, these games/matches are fairly predictable such as NFL games are played primarily on Sundays which allows clinicians and practitioners to plan training and recovery session accurately. However, in a sport like basketball in the NBA this becomes more difficult due to the amount of games, game density, and increased travel

demands. The NBA plays an average of 3.5 games per week without regularity unlike in other sports (Teramoto et al., 2017). This paper will explore a potentially more applicable of using the ACWR within basketball.

Methods

Literature Review

A thorough literature review was conducted to ascertain where the ACWR has been applied and if any modifications have ever been made to it. The literature review used the following databases: EBSCO, SPORTdiscus, PubMed, and Google Scholar for comprehension. The following parameters were used: years (2000-2024), keywords: 'Acute to Chronic Workload Ratio', 'Workload Ratio', 'External Workload'. The following search yielded 300 preliminary articles of which both authors evaluated them against the PRISMA scale and related tools (Page et al., 2021). 20 articles were included in article after implementation of the exclusion criteria.

The Modified ACWR

Since professional basketball in the United States has a unique and congested schedule consisting of 82 games (regular season) and played an average of 3.5 games per week, the authors propose a three-tiered modified ACWR system. This modified ACWR is potentially meant to better encompass the demands of professional basketball players and may serve as a more appropriate proxy for neuromuscular fatigue and injury risk.

Hypothesis

1) There will be no differences between the original ACWR and the modified ACWR as proposed by the authors.
2) There will be no significant differences between both ratios, set forth by a p-value of <0.05.

Results

The Practical Example

Original ACWR

For one player who is tracked via external workload monitoring their daily workload was 1000 arbitrary units (AU) and subsequently 5000 AU over one seven-day period which comprises the acute portion. Over a 28-day period, their cumulative workload was 23,000 AU in a standard 30-day month (split = Week 1: 5000, Week 2: 6000, Week 3 = 7000, Week = 5000). The ACWR in this case would amount to 23,000 AU/ 4 weeks = 5,750 AU; 5000 AU/ 5750 AU = 0.86

Modified ACWR

Acute Workload

The same daily workload of 1000 AU was used for this approach which would amount to 3000 AU (3 day)/ 5000 (7 Day) = 0.6

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
7_28_ACWR	9	.8600	.00000	.00000
3_7_ACWR	9	.600	.0000[a]	.0000

a. t cannot be computed because the standard deviation is 0.

One-Sample Test

	Test Value = 0						
			Significance			95% Confidence Interval of the Difference	
	t	df	One-Sided p	Two-Sided p	Mean Difference	Lower	Upper
7_28_ACWR	4.949E+16	8	<.001	<.001	.86000	.8600	.8600

Transient Workload

The same daily workload of 1000 AU was used for this approach which would amount to 5000 AU (7-day) / 6,500 (14 day) = 0.76

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
7_28_ACWR	9	.8600	.00000	.00000
7_14_ACWR	9	.7600	.00000	.00000

One-Sample Test

Test Value = 0

	t	df	Significance One-Sided p	Significance Two-Sided p	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper
7_28_ACWR	4.949E+16	8	<.001	<.001	.86000	.8600	.8600
7_14_ACWR	3.164E+16	8	<.001	<.001	.76000	.7600	.7600

Chronic Workload

The same daily workload of 1000 AU was used for this approach which would amount to 5000 AU (7-day)/ 6,000 (21 day) = 0.83

T-Test

One-Sample Statistics

	N	Mean	Std. Deviation	Std. Error Mean
7_28_ACWR	9	.8600	.00000	.00000
7_21_ACWR	9	.8300	.00000	.00000

One-Sample Test

Test Value = 0

	t	df	Significance One-Sided p	Significance Two-Sided p	Mean Difference	95% Confidence Interval of the Difference Lower	95% Confidence Interval of the Difference Upper
7_28_ACWR	4.949E+16	8	<.001	<.001	.86000	.8600	.8600
7_21_ACWR	6.949E+16	8	<.001	<.001	.83000	.8300	.8300

Statistics

The original ACWR resulted in a workload ratio of 0.86 and each modified approach in 0.6, 0.76, and 0.83 respectively. An ANOVA test was originally to be run since the authors were striving to compare 4 different groups (traditional vs acute, transient, and chronic). However, since there was only one 'case' per instance, t-tests were run on traditional vs each modified approach with a post-hoc correction to reduce to chance of correction significance. The 3:7 acute workload ratio could not be computed since the standard deviation was zero. The 7:14 transient workload ratio was significant ($p < 0.01$). The 7:21 chronic workload ratio was also significant ($p < 0.01$).

Discussion

This paper sought to challenge the traditional ACWR and its application to basketball due to various factors such as game frequency, game density, and overall different demands than what has explored in the literature (Tae Sung, n.d.). The traditional ACWR seeks to quantify injury risk on a more global level than only immediate (Maupin et al., 2020). This is based off the work by Bannister and Gabbett that an athlete can be overstimulated or under stimulated. The optimal range of work seems to lie between 0.8-1.3, less than 0.8 may lead to under stimulation while more than 1.3 may lead to overstimulation (Williams et al., 2016). Both scenarios can lead to an increased injury risk because either an athlete does not have enough exposure to stress or too much exposure (under recovery). However, this approach to injury may be too general to the sport of basketball. As seen in the sample calculation, the traditional ACWR was 0.86 which would fall

within the 'sweet spot' from 0.8 – 1.3 (Andrade et al., 2020). It is interesting to note that findings from the 3:7 and 7:14 ratios would result in under stimulation of the athlete from a training demand standpoint which highlight discrepancies between each approach. Thus, practitioners may actually recommend supplemental training or conditioning in this scenario to keep the athlete prepared for sport.

Within the traditional ACWR approach, there are two main derivatives: rolling average (RA) and exponentially weighted moving average (EWMA). The RA approach uses the absolute workloads accumulated in one week (i.e. 7 days) to the absolute workload accumulated in four weeks (i.e. 28 days) (Menaspà, 2017). This approach assumes a linear relationship between work performed on day 1 and day 28, which is disputed by the fitness-fatigue paradigm. The EWMA model seeks to overcome this by placing more weight on the most recent training sessions (loads) through a weighted formula (Murray et al., 2017). Although this model does provide a more realistic value of athletic workload, it may still not meet demands of a professional basketball schedule.

Griffin et al. (2020) wrote a systematic review pertaining to the ACWR and its application to team sport (Griffin et al., 2020). This study focused on the ACWR use for injury risk prediction and increased workloads. The authors found the EWMA model to be more sensitive in predicting injury risk for team sports in general. Two key points highlighted include that the most appropriate time periods for ratios should be specific to the sport which was explored in the current paper. Also, the importance of building resiliency in athletes through workloads over longer periods of time. Hulin et al. (2016) explored rugby specifically and three approaches to injury risk: acute workload, chronic workload, and the ACWR (Hulin et al., 2016). The authors found that a combination of acute to chronic serves as a more specific measure of injury which is based on the premise of being able to capture data points from different time periods. Furthermore, high chronic workloads with moderate acute workloads tend to be protective while it is the spike in acute workloads that should met with caution when seen by practitioners. The findings from this study highlight how ratios can be specific to seeing injury risk over time, however the amount of time into the sport of basketball is still undecided.

In the book 'Basketball Sports Medicine and Science' by Laver et al. (2020), Tim Gabbett has a chapter named 'Load Management in Basketball' (Laver et al., 2020). Gabbett defines external load as the amount of work performed by an athlete or athletes. He explains a three-dimensional model balanced by load, load capacity, and athlete health. Load and load capacity are the two most investigated pieces of the model because load is straightforward to understand along with load capacity. However, practitioners should not overlook athlete health since objective data can only take one so far when working with humans. As one example, the same objective load of 800 AU may be handled very differently by the same athlete on two separate days. The interesting part about the chapter is that Gabbett, who is a pioneer in the field of the ACWR proposes an intensity (RPE scale of 0-10) multiplied by duration for a measure of Weekly Load. Additionally, Monotony can is the average weekly load/ SD of weekly load and Strain is the product of weekly load and monotony. It is interesting that although the AWCR is mentioned, it is not adopted into the schedule and demands of basketball.

Weiss et al. (2017) specifically looked at the relationship between training load and injury in men's professional basketball (Weiss et al., 2017). The method used was traditional in average weekly load divided by the average of an accumulated four-week load. To supplement workload ratios, regressions were also run against injury data to explore potential relationships. The authors found the fewest amount of injuries occur within the range of 1.0-1.49 vs lower values (potential under stimulation) and higher values (potential over stimulation). While this study seems to serve as concrete evidence for traditional ACWR, data collection was performed sRPE multiplied by duration of training session or game to obtain load. Injuries were tracked by the athlete themselves via online survey. These findings should be interpreted with caution since workload was not standardized to the team as using external load monitors (GPS, LPS), instead each player may have different perceptions of 'difficulty' and skew the final data. Also, from an injury tracking standpoint, athlete recall may have compromised true injury rates along with potential deception about injury status due to wanting to play vs if a team physiotherapist would have documented injuries daily.

Anderson et al. (2003) investigated injury and incidence rates in Women's basketball throughout an NCAA Division 3 season (Andersen, 2000). This article considered training load, training monotony, and training strain along with injury/illness via questionnaire. 'Session load' was the product of session RPE and session duration which was then averaged over a 4-week period. Training monotony was calculated from the mean training load divided by the standard deviation of the training load over a 1-week period. Lastly, training strain was calculated as the product of training load and training monotony. The Pearson Product Moment correlation was performed to explore relationships between training load and injury/illness. The authors found a moderate relationship ($r = 0.675$) between training load and injury. Specifically, both training loads and injury increased during the first 2 weeks of practice and right after the holidays. These findings show the duality of training load which can be too little or too much stress However, this study faces the same limitations as Weiss et al. (2017) in that session load was performed with an sRPE scale and injury surveys were self-performed by the athlete (Weiss et al., 2017). Furthermore, although a temporal relationship was defined, it is difficult to know how other time frames may have affected the findings.

Wang et al. 2020 investigated why using a workload ratio may not be the optimal approach to injury risk (Wang et al., 2020). The authors explain the difficulty in maintaining consistency when quantifying training load as different sports

have different metrics. This is true as it pertains to basketball since training is split into its own schema not identical to other sports (set pieces, half-court play, full-court live play, etc.). This was seen by the authors of this paper where even in basketball related research, loads were tracked using a subjective method and injuries were poorly defined due to self-survey collection. Overall, Wang et al. (2020) cautions against using the ACWR approach alone which the authors agree with. When working with humans, it is impossible to truly quantify how much work each athlete is doing and how their individual physiology responds to said stress. Thus, practitioners should strive to place together an athletic ecosystem that is multi-faceted rather than placing all eggs in one baskets so to speak.

Conclusion

Due to unique nature of travel, game density, and game frequency it is difficult for one workload ratio to fully encompass injury risk and decrements in physical performance in the NBA (Charest et al., 2021). This paper sought to bring a modified approach through 3 unique workload ratios. Practitioners can then have the option of choosing one or all ratios that best suit their needs. For example, acute spikes in workloads need to have larger deviations from the mean while chronic spikes can be more moderate while have the same deleterious effect on performance. By having three ratios, practitioners can look at player loads in a more holistic manner and make more informed decisions. The results of this study may be used to make weekly plans or game cluster plans in training, recovery, and stimulus adaptations. The primary limitations of this paper are the lack of subjects since this study is meant to serve as a proof of concept. In the future, it would be prudent to follow a team over a season and look at factors like fatigue, performance, and injury risk comparing the traditional ACWR vs each modified approach. The heuristic methods of this paper have been applied in unofficial manners and practitioners may choose to adapt versions of different workload ratios to better suit their athletes' needs.

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