Calculating The Acute: Chronic Workload Ratio In A Female Olympic Weightlifter: A Case Study

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Current Position Bio

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Abstract

Introduction: The idea of workload monitoring has become popular for athletes of all levels within the last 5 years with the advent of wearable technology. The purpose of this case study was to track the workload of a female Olympic weightlifter using a commercial fitness tracker.

Methods: A competitive, female Olympic Weightlifter wore a commercial fitness tracker (WHOOP) for 1 month and specifically during training session. Metrics like strain, average heart rate (HR), max HR, and duration of session were tracked. The acute: chronic workload ratio was also calculated based off her programming. 2 sample t-tests were calculated between continuous variables and an ANOVA was performed between multiple continuous variables. Statistical significance was set as a p-value of (<0.05) using a confidence interval of 95%.

Results: The WHOOP fitness tracker was able to calculate differences between strain and HR average ($p<.001$), between HR average and HR max ($p<.001$), HR average and Workload ($p<.001$), and HR max and Workload ($p<.003$). ANOVA analysis showed a p-value of (<.001) between all continuous variables. The acute: chronic workload ratio over the 4 weeks ranged from (0.85-1.10).

Conclusion: Using wearable technology has become a cost-effective and efficient technique to track athlete workload even in the recreational population. This information can then be supplemented by acute: chronic workload ratios for more information. This can lead to clinicians, coaches, and athletes having higher quality information to improve sports performance and recovery while mitigating the risk of injury.

Key Words: Workload Monitoring; Workload Ratios; Wearable technology; Heartrate Monitor; Olympic Weightlifting

Introduction

The idea of workload monitoring for athletes and teams was popularized largely due to the work of Dr. Tim Gabbett in rugby players[1]. Implementing the idea of an Acute: Chronic Workload Ratio (ACWR), a coach or clinician can track trends in workload within their athlete population[2]. The ACWR is part of literature that is meant to enhance sport performance while mitigating injury risk[3,4]. For example, a very low workload will not yield positive adaptations while high workloads may lead to psychological fatigue and injury[5,6]. The literature supports a “sweet spot” of 0.8-1.3 ACWR as a general guideline for optimal workloads[7].

The idea of workload monitoring however with the advent of modern technology has extended into recreational athletes and is very popular in the running community[8–10]. For example, wearable technology has made tracking metrics such as strain, sleep, Heart Rate (HR), and recovery user friendly and cost-effective. Commercial companies such as Polar[11], Apple[12], Fitbit[13], and WHOOP fitness tracker[14] all have this wearable technology.

A majority of the literature for wearable technology has followed running sports (long distance) and GPS technology is available to track Football and Soccer to see how much ground is covered in a training session.

GPS technology allows gathering of additional metrics such as time is speed zones, maximum speed, and player intensity[15]. However, the literature in other sports such as Olympic Weightlifting has not been investigated to date.

Olympic Weightlifting is a unique sport because athletes are essentially static through their entire training session with the exception of moving around their weightlifting platform or minute changes in their stances[16,17]. This sport is characterized by two lifts: The Snatch and The Clean and Jerk which are described in more detail in the work by Serrano and Serrano[18].

The purpose of this case study was to quantify the workload of a female, competitive Olympic Weightlifter using two user friendly methods: ACWR and the WHOOP Fitness Tracker. The authors hypothesized both methods would provide valid information in the recreational environment that would be easy to track and calculate.

Methods

This subject for this case study was a 34-year old Asian-American competitive weightlifter who trains 5-6 times per week. At the time of writing this case study; she had no musculoskeletal, orthopedic, or neurological injuries that may have hindered her ability to train. Through her health screening, she denied any history of osteoporosis, autoimmune disease, or endocrine abnormalities. The patient was explained all aspects of the study including: her responsibility, the duration of the study, and any risks associated with the study before being enrolled and consented into the study which was IRB (Institutional Review Board) approved.

The case study took place over a mesocycle of 4 weeks in the month of June 2020 as the case athlete was preparing for a national level meet in September 2020 through USA Weightlifting which is the governing body for the sport in the United States.

The WHOOP fitness tracker is a wearable technology band that resembles a bracelet and was worn by the athlete throughout the duration of the study for data collection. She gave the log-in information to both members of the study staff which was transferred into a password protected laptop onto an excel spreadsheet. Only data from 06/01/2020-06/30/2020 was accessed as to not invade the athletes privacy any more than necessary. Once data collection was complete, the athlete was notified so she could change log-in and password if she pleased for privacy purposes.

Programming was obtained from the Weightlifting coach with permission from the athlete and included: Exercises, Weight, Set, Reps, and total volume for the training session. Any pertinent questions regarding programming were directed at either the Athlete or Coach.

Statistics

The Shapiro-Wilks test was used to measure normal distributions between the variables measured. The independent samples *t*-test was used to measure relationships between continuous variables. An ANOVA analysis was performed to measure relationships between the multiple continuous variables measures. Significance levels were set at $p<.05$ with a confidence interval of 95%.

The ACWR was measured as set forth by Hulin et al.[1] which is summarized as calculating the workload over a certain time period such as week (acute) then followed by the workload over the entire time period desired such as one month (chronic) and dividing it for the ACWR.

Results

The athlete used in the study was a 32 year old female Olympic Weightlifter who is currently training for a national competition in September 2020. She was tracked for the entire month of June 2020 which resulted in 29 days of data which were included in the final analysis.

The WHOOP fitness tracked 4 different metrics: Strain, HR Average, HR Max, and Duration (Minutes) which is summarized in Table 1.

Table 1: Resulting Metrics from WHOOP Fitness Tracker

	Week 1	Week 2	Week 3	Week 4
Strain	9.43	8.07	8.44	9.09
HR Average (BPM)	112	105	107	109
HR Max (BPM)	152	152	156	153
Duration (Minutes)	105.14	103.71	115.14	115.71

Independent Sample *t*-tests were run on the continuous variables to determine if a significant difference existed and resulted in statistical significance between all variables. Strain and HR Average ($p<.001$), HR Average and HR max ($p<.001$), HR Average and Duration of the workout ($p<.001$), HR Average and Workload ($p<.003$). The ANOVA: Single Factor Analysis resulted in a value of ($p<.001$) between groups for statistical significance.

The ACWR was calculated using the data is Figure 2 and showed values ranging from 0.85-1.10 through the 4 week mesocycle.

Table 2: Acute to Chronic Workload Ratio

Acute Workload	Chronic Workload	A:C Workload Ratio	
Week 1: 8155	7429.25	Week 1: 1.10	
Week 2: 8102		Week 2: 1.09	
Week 3: 6336		Week 3: 0.85	
Week 4: 7124		Week 4: 0.96	

Discussion

This case study followed the mesocycle of a competitive Olympic Weightlifter for one continuous month in preparation for a National level meet. The two methods used to track data were the WHOOP fitness tracker and calculating the ACWR. Wearable technology has become a popular and cost-efficient way of tracking physiological metrics[19–21] . For example, Appleboom[22] investigated wearable technology in patients with chronic health disease morbidity predictors such as blood pressure, heart rate, body temperature as well as data related to exercise, diet, and psychological state. Lableau[23] investigated physical activity in patients total joint replacement using an electronic tablet. De Zambotti[24] used a fitness tracker (Jawbone Up) to validate sleep in adults vs polysomnography. In professional sports, the use of GPS[25,26] and accelerometers[27–29] are used to track workload and distances covered during training/game sessions. The concept of load management has even become joint specific depending on sport. For example, Motus (Motus Global) has developed wearable sleeves for the overhead athlete (Motus Throw) to capture the volume and torque produced at the elbow during the throwing motion[30–32].

Similar to wearable technology, the ACWR has been validated in the literature as a method for tracking workload ratios[1,7,33]. It is different from wearable technology in that ACWR seeks to compare the chronic workload of an athlete to their acute workload. There should be no spikes in the ratio which may predispose an athlete to an increased risk of injury[34,35] . The sweet spot of workload ratio has been proposed to be 0.8-1.3[36,37]. A ratio under 0.8 does not elicit the proper stimulus for sports performance while ratios over 1.3 may cause psychological and physiological fatigue resulting in injury.

The metrics captured by the WHOOP fitness tracker were all statistically significant when compared using a two-sample t-test which supports the objectivity of being able to track metrics such as strain, HR average, HR max, and duration of workouts. The ACWR was accurate in calculating workload ratios. This is the first study known to the authors using these methods to track workload in the sport of Olympic Weightlifting and does support its use as a user friendly and cost-efficient method of tracking workload.

Limitations

This study is limited by its nature as a case study which includes one subject and greatly limits the external validity. This study used the WHOOP fitness tracker to capture various metrics, however other technology could have been used with unknown results. Even though the purpose of this case study was feasibility in capturing workload metrics, it may have been strengthened by comparison with other wearable technologies. Similarly, the ACWR was calculated using previous information in the literature but was not tracked by a more validated program. The total workload could have also been miscalculated by the coach or study staff. The methodology of this case study relied on data tracked by the subject which may have been variable in exercise intensity or effort put into the training session by knowing her metrics were being tracked. Lastly, a biopsychosocial questionnaire was not performed on the subject to ensure her state of mind during each training session which may account for training session variability.

Conclusion

The use of wearable technology has increased greatly in the past 10 years that began in professional sports but is now being used by teams and athletes of all levels. This case study tracked a competitive Olympic Weightlifter over 1 month using the WHOOP fitness tracker and calculating ACWR. It may be distracting to wear extra instruments during weightlifting which fortunately was not the case using the WHOOP fitness tracker. The information resulted in being able to easily track metrics such as strain, heart rate, and duration of workouts along with ratios to guide clinicians and coaches in programming and optimizing performance for athletes they work with. Future studies should expand on these findings by incorporating entire Weightlifting clubs and teams at various levels of competition. Interestingly, no injuries were reported during the time period which corresponds to the literature of keeping the ACWR between 0.8-1.3. This case study is the first known study to track workloads using two different methods in the Olympic Weightlifter which will aid in understanding this growing sport.

Practical Applications

Wearable technology has become a cost-effective and user-friendly of tracking metrics in competitive and recreational athletes. In the sport of Olympic Weightlifting, training sessions may last up to 2.5 hours that consist of the two main lifts, variations, and accessory work. The ability to track internal and external workload is promising for the coach and clinician who work with Weightlifters in order to optimize sport performance and recovery while mitigating risk of injury.

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