Relationship Between Heart Rate Variability and Acute:Chronic Load Ratio Throughout a Season in NCAA D1 Men's Soccer Players

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Abstract

Sekiguchi, Y, Huggins, RA, Curtis, RM, Benjamin, CL, Adams, WM, Looney, DP, West, CA, and Casa, DJ. Relationship between heart rate variability and acute:chronic load ratio throughout a season in NCAA D1 men's soccer players. *J Strength Cond Res* 35(4): 1103–1109, 2021—The purpose of this study was twofold: (a) to examine the relationship between heart rate variability (HRV) and acute:chronic workload ratio (ACWR)-based training load (TL) metrics and (b) to examine relationships across various A:C ratio-based TL metrics. Heart rate variability in 23 male college soccer players (mean ± *SD*; age, 21 ± 1 years; body mass, 80.3 ± 5.8 kg; height, 181.9 ± 6.5 cm; %body fat, 11.9 ± 2.0%; and $\dot{V}O_2$max, 51.9 ± 5.0 ml·kg^{-1}·min^{-1}) was measured at 5 time points: week(W)1, W3, W7, W12, and W14 during the 2015 NCAA men's soccer season. Heart rate variability was calculated from beat to beat intervals using a heart rate monitor. Players donned a global position satellite–enabled device that measured the following TL metrics: session time (ST), Player Load (PL), PL·min^{-1}, and total distance (TD). Acute:chronic workload ratio was calculated for each TL metric: ACWR-based ST ($ACWR_{ST}$), ACWR-based PL ($ACWR_{PL}$), ACWR-based PL·min^{-1} ($ACWR_{PLM}$), and ACWR-based TD ($ACWR_{TD}$): ACWR = week average TLs/mo average (30 ± 1 days) TLs. Relationships between HRV and ACWR-based each TL metric were evaluated using mixed effects models. Tukey pairwise comparisons were used to examine differences between types of ACWR-based TL metrics. An increase in $ACWR_{ST}$ significantly reduced HRV throughout a season (−7.4 ± 3.6 m·s^{-1}; p = 0.04). There were significant differences between $ACWR_{PLM}$ and $ACWR_{ST}$, $ACWR_{PL}$ and $ACWR_{TD}$ at W1, $ACWR_{PLM}$ and $ACWR_{ST}$ at W3 ($p < 0.05$). In conclusion, $ACWR_{ST}$, $ACWR_{PL}$, and $ACWR_{TD}$ were significantly different from $ACWR_{PLM}$. $ACWR_{ST}$ was found to significantly predict HRV; higher $ACWR_{ST}$ was significantly associated with lower HRV. Therefore, tracking of the ACWR using ST may help to optimize athlete's physiological state throughout a season.

Key Words training load management, cardiac autonomic system, preparedness, exercise performance

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Introduction

Achieving peak performance in sport is crucial for obtaining desirable results and requires optimal training and preparation for athletes to excel during competition. Coaches, sports scientists, and medical personnel have been attracted to monitoring athletes' training load (TL) through a global position satellite (GPS) monitoring (36), session rating of perceived exertion (RPE) (21), perceived fatigue (35), performance testing (15), and biomarkers (3), and to evaluate adaptations to training and accumulated fatigue for making data-driven decisions to maximize athlete performance and prevent injury (34).

Heart rate variability (HRV) is an example of a noninvasive method used to monitor changes in cardiovascular regulation, which is regulated by autonomic activation of the sympathetic and parasympathetic pathways (2). Changes in HRV is highly related to overall training adaptations and physiological state such as readiness (2,5,7,23,38), with data showing that an increased maximal oxygen consumption is associated with an increase in HRV (29). Also, athletes with increased HRV before the start of training demonstrated improved performance after training compared to athletes with decreased HRV (38). Overtraining in swimmers reduced HRV (−5.6%) compared with baseline values; however, as HRV decreased over time, values returned to baseline or peaked during tapering periods, leading to successful

Table 1. Heart rate variability data collection sequence.*

Date	Timing of HRV measurement	Week
August 14	Two days before the first pre-season match	1
August 26	Two days before the first regular season match	3
September 24	Two days before the 8th regular season match	7
October 29	Two days before the final regular season match	12
November 17	Two days before the first NCAA tournament match	14

*HRV = heart rate variability.

competitions (12). Thus, HRV as heart rate–derived markers of autonomic nerve system (HR-ANS) have demonstrated associations with exercise performance and fatigue.

Athlete's TLs are also related to exercise performance and HR-ANS. Extremely high TLs may result in accumulated fatigue and potentially overtraining syndrome, which may lead to performance decrements and chronic maladaptation (1,34). One quantifiable method exhibiting promise in the detection of overtraining, fatigue, and onset or risk of injury is the use of the acute:chronic workload ratio (ACWR) that uses session time (ST), RPE, and distance covered as TL (4,13,14,18–20,34). If when chronic TL is progressively increased to high level, athlete's fitness can be increased, which leads to experiencing minimal fatigue caused by acute TL (34).

When the ACWR was above 1.5, the risk of injury was 2–4 times greater within the next 7 days (13). The theory for this phenomenon is that the ACWR provides information about whether the athlete's acute TL is greater, less than, or equal to the TL that the athlete has been prepared for during the chronic period (20), and when acute TL is higher than the level that athlete is ready to tolerate, acute TL increases in fatigue and the risk of injury (34). Thus, the ACWR is potentially associated with the athlete's HR-ANS, although it is currently only used for injury prevention purposes.

Heart rate variability is routinely assessed throughout training to measure an athlete's HR-ANS as a noninvasive and easy method. Because the ACWR has been associated with fatigue, the ACWR could influence on HR-ANS. However, no studies have examined the relationships between HRV and the ACWR. Previous researches have examined the ACWR-based various TL metrics, such as distance covered, RPE, and ST. However, no study has investigated the relationships between the ACWR-based various TL metrics. Thus, the first purpose of this study was to examine the relationship between HRV and ACWR-based various TL metrics in collegiate soccer. Also, the second purpose of this study was to examine the relationship across various TL metrics from which the ACWR can be calculated in collegiate soccer.

Methods

Experimental Approach to the Problem

This study was an observational investigation designed to examine (a) the relationship between HRV and the ACWR-based various TL metrics, (b) the relationships among various ACWR-based TL metrics, in Division 1 male collegiate soccer players. Resting HRV was measured 2 days before scheduled match play at 5 time points throughout the competitive season. Training load metrics, such as ST, Player Load (PL), $PL \cdot min^{-1}$, and total distance (TD) during exercise, were also monitored during all practices and matches to

Table 2. Mixed effects model prediction of HRV by ACWR-based TL metrics.*†

	Intercept ($m \cdot s^{-1}$)	Slope ($m \cdot s^{-1}$)	p	Error
$ACWR_{ST}$ (au)	106.8 ± 9.4	−7.4 ± 3.6	0.044‡	40.7
$ACWR_{PL}$ (au)	105.8 ± 9.3	−6.9 ± 3.6	0.060	40.8
$ACWR_{PLM}$ (au)	102.3 ± 9.3	−4.7 ± 4.0	0.245	41.3
$ACWR_{TD}$ (au)	105.6 ± 9.2	−6.9 ± 3.6	0.059	40.8

*HRV = heart rate variability; ACWR = acute:chronic workload ratio; TL = training load.
†Acute:chronic workload ratio–based session time ($ACWR_{ST}$), Player Load ($ACWR_{PL}$), $PL \cdot min^{-1}$ ($ACWR_{PLM}$), and total distance ($ACWR_{TD}$).
‡Significant predictor of HRV.

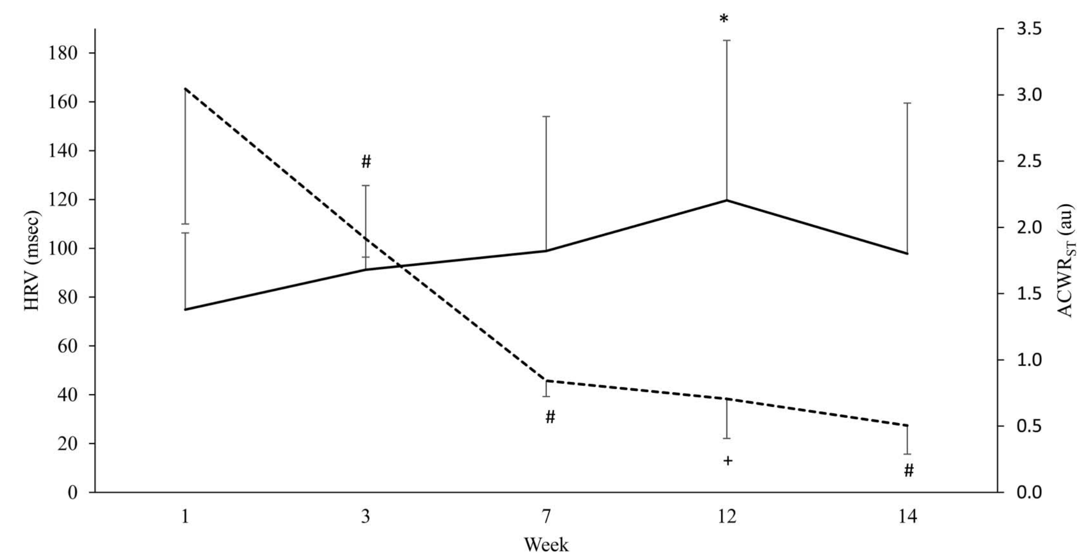

Figure 1. $ACWR_{ST}$ (dotted line) and HRV (solid line) over the course of season. *Different ($p < 0.05$) from W1; #different ($p < 0.05$) from previous time point; and +different ($p < 0.05$) from W7 and W3. $ACWR_{ST}$ = acute:chronic workload ratio–based session time; HRV = heart rate variability.

calculate ACWR-based ST ($ACWR_{ST}$), ACWR-based PL ($ACWR_{PL}$), ACWR-based $PL \cdot min^{-1}$ ($ACWR_{PLM}$), and ACWR-based TD ($ACWR_{TD}$).

Subjects

Twenty-three male Division 1 collegiate soccer players (mean ± *SD*; age, 21 ± 1 years; body mass, 80.3 ± 5.8 kg; height, 181.9 ± 6.5 cm; body fat, 11.9 ± 2.0%; and $\dot{V}O_2max$, 51.9 ± 5.0 $ml \cdot kg^{-1} \cdot min^{-1}$) participated in this study, which took place during the 2015 NCAA men's soccer season. After an explanation of the study's procedures, risks and benefits of the study, subjects provided written informed consent to participate in this study, which was approved by the University of Connecticut Institutional Review Board. No players were younger than 18 years.

Procedures

Resting heart rate data were collected (Polar Team 2; Polar Electro, Lake Success, NY) with players lying in a supine position for 10 minutes in a dark room between the hours of 0600 and 0800 in the morning 2 days before scheduled match play at 5 time points (August 14, week (W) 1; August 26, W3; September 24, W7; October 29, W12; and November 17, W14) during the 2015 NCAA men's soccer season (Table 1). Players were asked to come to the laboratory in a fasting state on wakening. In addition, players had not exercised for the previous 24 hours and were told to maintain normal drinking behavior. To further minimize any confounding factors that may disrupt HRV measures, only 5 subjects were measured at a time. The root mean square of successive R-R intervals (HRV; RMSSD) (32) was calculated from beat to beat intervals (Polar Team 2; Polar Electro Oy, Kempele, Finland).

Training load metrics (ST, PL, $PL \cdot min^{-1}$, and TD) were monitored daily during all practices and matches using GPS-enabled wearable monitor positioned on the midscapular region of all players (Catapult Minimax X S4 and L5, Catapult, Australia). Instantaneous PL (PL_i) was calculated by the following equation:

$$PL_i = \sqrt{(lng_{t=i+1} - lng_{t=i})^2 + (lat_{t=i+1} - lat_{t=i})^2 + (ver_{t=i+1} - ver_{t=i})^2},$$

where *lng* is the acceleration in the longitudinal axis, *lat* is the acceleration in the lateral axis, *ver* is the acceleration in the vertical axis, and *i* is the present time. The accumulated PL was calculated as the summation of all PL_i values recorded over an exercise divided by a scaling factor of 100 (6,9). Session time, PL, and TD are accumulated TLs, and they represent training volume; however, $PL \cdot min^{-1}$ represents training intensity.

Table 3. Relationship between the ACWR-based TL metrics.*†

r	$ACWR_{ST}$ (au)	$ACWR_{PL}$ (au)	$ACWR_{PLM}$ (au)
$ACWR_{ST}$ (au)			
$ACWR_{PL}$ (au)	0.99‡		
$ACWR_{PLM}$ (au)	0.92‡	0.95‡	
$ACWR_{TD}$ (au)	0.98‡	0.99‡	0.93‡

*ACWR = acute:chronic workload ratio; TL = training load.
†Acute:chronic workload ratio–based session time ($ACWR_{ST}$), Player Load ($ACWR_{PL}$), PL·min^{-1} ($ACWR_{PLM}$), and total distance ($ACWR_{TD}$).
‡Significant ($p < 0.05$) relationship between variables using Pearson product-moment correlations.

The ACWR was calculated for each TL metric by the following equation: ACWR = week average TLs/mo average (30 ± 1 days) TLs, such as the average of 7/15–8/14 for W1. Days in which the team had a scheduled "off" day (no team activities took place), TL for that day received a value of 0. Some players trained before the start of pre-season and those TLs were also captured; however, players who did not train with team on campus at all before a pre-season had a value of 0. These data were used when the ACWR for W1 was calculated. For practice, no data were excluded or extracted from any of the training sessions; therefore, all calculated metrics come from the entirety of the athlete wearing the device that day. For matches, off-filed activity was excluded, and players who did not play in matches had a value of 0.

Statistical Analyses

Relationships between HRV (dependent variable) and the ACWR-based each TL metric (independent variables) were evaluated using mixed effects models that included random effects of the subject on intercepts. This analysis was performed using RStudio Version 0.98.1056 (c 2009-2013RStudio, Inc.).

Data are presented as mean ± *SD*, mean differences (MDs), and 95% confidence intervals (95% CIs). Effect size (ES) was also measured using Cohen's *d* with the resulting effects identified as either small (0.2–0.49), medium (0.5–0.79), or large (>0.8) effects (25). Separate repeated-measures analysis of variance (ANOVA) with subsequent post hoc analyses of an adjustment for multiple comparisons of Bonferroni was used to determine differences in HRV. Separate repeated-measures ANOVA with Tukey pairwise comparison was used to detect the differences between the ACWR-based TL metrics across each time point and also the differences between types of ACWR-based TL metrics. Pearson product-moment correlations were used to calculate the relationship between various ACWR over the season. These statistical analyses were performed using SPSS (version 21; IBM Corporation, Armonk, NY). Significance was set at a priori at $p \leq 0.05$.

Results

An increase in $ACWR_{ST}$ resulted in a significant reduction in HRV throughout a season (-7.4 ± 3.6 m·s^{-1}; $p = 0.04$) (Figure 1 and Table 2). Heart rate variability at W12 was significantly higher than W1 (MD [95% CI]; 44.8 m·s^{-1} [14.2, 75.3], $p = 0.026$, ES = 0.87). However, there were no differences in HRV at any other time points across the season ($p > 0.05$).

Pearson product-moment correlations showed that there were significant associations between the various ACWR-based TL metrics ($r = 0.92$–0.99, $p < 0.05$, Table 3). Table 4 presents the changes in ACWR-based TL metrics over the

Table 4. The ACWR-based TL metrics.*†

	1	3	7	12	14
$ACWR_{ST}$ (au)	3.0 ± 1.0	1.9 ± 0.1^{1}	0.8 ± 0.1^{1,3}	0.7 ± 0.3^{1,3}	0.5 ± 0.2^{1,3,7}
$ACWR_{PL}$ (au)	3.0 ± 1.2	1.8 ± 0.2^{1}	0.8 ± 0.2^{1,3}	0.7 ± 0.3^{1,3}	0.5 ± 0.3^{1,3,7}
$ACWR_{PLM}$ (au)	2.4 ± 1.6‡	1.6 ± 0.3§^{,1}	1.0 ± 0.1^{1,3}	0.8 ± 0.3^{1,3}	0.5 ± 0.2^{1,3,7,12}
$ACWR_{TD}$ (au)	2.9 ± 1.1	1.8 ± 0.2^{1}	0.8 ± 0.2^{1,3}	0.7 ± 0.3^{1,3}	0.4 ± 0.4^{1,3,7,12}

*ACWR = acute:chronic workload ratio; TL = training load.
†Acute:chronic workload ratio–based session time ($ACWR_{ST}$), Player Load ($ACWR_{PL}$), PL·min^{-1} ($ACWR_{PLM}$), and total distance ($ACWR_{TD}$). (^{1,3,7,12}) = significant difference from the time point within each ACWR-based TL metrics ($p < 0.05$).
‡Significant difference between $ACWR_{PLM}$ and $ACWR_{ST}$, $ACWR_{PL}$ and $ACWR_{TD}$ at W1 ($p < 0.05$).
§Significant difference between $ACWR_{PLM}$ and $ACWR_{ST}$ at W3 ($p < 0.05$).

course of the season. Acute:chronic workload ratio decreased over the course of the season in all ACWR-based TL metrics ($p < 0.05$).

Discussion

The primary purpose of this study was to examine the relationship between HRV and ACWR-based various TL metrics. Our results indicate that there was a significant negative relationship between HRV and the $ACWR_{ST}$. Thus, an acute decrease of ST was associated with increased HRV. The secondary purpose of this study was to examine the relationship across various ACWR-based TL metrics in collegiate soccer. Acute:chronic workload ratio–based TL metrics were highly related to each other, and our findings suggest that over the course of the season, ACWR-based TLs decreased. Interestingly, we also found that the $ACWR_{PLM}$ was significantly lower than the $ACWR_{ST}$, $ACWR_{PL}$, and $ACWR_{TD}$ at W1, and the $ACWR_{PLM}$ was significantly lower than the $ACWR_{ST}$ at W3. To the best of our knowledge, this is the first investigation to explore relationships between ACWR and HRV, and examine the relationships between ACWR-based various TL metrics.

Heart rate variability analysis is a tool for assessing the degree of fatigue (33). Previous research has demonstrated that a recovery period after intense training increased HRV, indicating an abrupt compensation (33). Thus, increased HRV is a potentially sensitive indicator of dissipating accumulated fatigue (28) and better physiological state (5). In the current study, acute decrease of ST led to dissipating fatigue and an increase in HRV.

Heart rate variability increased gradually from the beginning of the season and peaked at W12, which was significantly higher than W1 (Figure 1). Acutely reducing the physiological and psychological stress of training is a potential mechanism to improve exercise performance (27). An example of this in the current study was the $ACWR_{ST}$ observed from W7 to W12 (0.7 ± 0.3). Training loads, indicated by ST, in these weeks were reduced, which was evident by the increase in HRV (Figure 1).

At the beginning of the season, as expected, the $ACWR_{ST}$ (1.9 ± 0.1 at W3) was elevated due to low chronic TL. Higher acute relative to chronic TLs are often used to induce positive training adaptations (33). For example, high-intensity training with a subsequent recovery period has led to performance enhancements in cyclists (10). Previously, although workload was increased relative to the previous period, HRV did not demonstrate a statistical significant change (31). A similar trend was observed in the current study, as HRV was not significantly different between W1 and W3.

At W14 compared with W12, HRV was slightly decreased, although it was not statistically significant. This might be due to a longer period of insufficient volume and intensity of training and a prolonged recovery (33). An insufficient training stimulus could induce detraining, which is a partial or complete loss of training-induced physiological and performance adaptation (27), and detraining can decrease HRV (16).

However, some researchers showed that HRV was not changed by overtraining. Hedelin et al. demonstrated that short-term overtraining in cross-country skiing did not affect HRV (17), and Uusitalo et al. (37) demonstrated that exhaustive training for 6–9 weeks did not cause a change in cardiac autonomic modulation in endurance athletes. The joint consensus statement of the European College of Sport Science and the American College of Sports Medicine suggests that there are inconsistent results of the relationships between HRV and overtraining (26). The reason for these inconsistencies remains unclear. However, one potential reason is that HRV is multifactorial (11) and factors besides overtraining could influence HRV. For example, many stress sources and negative emotions could induce low HRV (11). Depression has been associated with decreases in HRV (22). Collegiate athletes are a unique population who has potential outside factors (academic, social life, living away from family, etc.) that could influence HRV and should be considered when using HRV in a college setting.

The secondary purpose of this study was to examine the relationship across various metrics from which ACWR can be calculated in collegiate soccer. The $ACWR_{ST}$, $ACWR_{PL}$, and $ACWR_{TD}$, which represented training volume, were not different from each other, but the $ACWR_{ST}$, $ACWR_{PL}$, and $ACWR_{TD}$ differed from the $ACWR_{PLM}$, which represented training intensity. Previous studies used different TL metrics, such as distance (20), speed (8), and RPE (24) to calculate the ACWR. However, no study has shown the relationship between the ACWR of different TL metrics. The results from this study might indicate that when GPS is not available, measuring ST might be a useful tool to assess TL, instead of PL or distance covered during practices and matches. For monitoring TLs, especially with GPS, a team needs time, money, and human resources (30); thus, this method of assessing TLs could be useful for teams without the necessary resources.

Heart rate variability and the ACWR were measured at only 5 time points during the season, which was a limitation of this study. In addition, information about players who were away from campus before the pre-season was not captured. Other research measured HRV more frequently to fully understand the subtle changes of the autonomic nervous system (28). Moreover, some factors, other than TLs, might also influence HRV, such as stress, mood, and fatigue from outside of exercise (11). A study that will incorporate these factors into examining the effect of HRV is needed in the future to fully understand HRV changes throughout a collegiate soccer season. In previous research, the ACWR was only used for an injury prevention purpose; thus, more studies are needed to fully understand how ACWR is related to the HR-ANS.

In conclusion, $ACWR_{ST}$, $ACWR_{PL}$, and $ACWR_{TD}$ were not different; however, these variables differed from the $ACWR_{PLM}$. Furthermore, only $ACWR_{ST}$ was associated with changes in HRV. Higher $ACWR_{ST}$ was significantly associated with lower HRV, and acute increase in soccer training time might decrease the HR-ANS. Therefore, the ACWR as determined by ST might be a possible tool to use to manage TLs, with the ultimate goal being to improve the athlete's HR-ANS.

Practical Applications

Tracking the ACWR using the ST may help to optimize an athlete's HR-ANS over the course of a season. This study suggested that acute increases in training time may lead to a reduction in HRV. To improve an athlete's HR-ANS for optimal physiological state, shortening STs may induce these changes; however, considerations should be made surrounding the outside factors that can also influence the HR-ANS. Moreover, when GPS is not available, monitoring ST can be used to monitoring changes in TL throughout a season. This could allow coaches and sport scientists to calculate and use the $ACWR_{ST}$ without GPS analysis. Measuring ST, as opposed to GPS monitoring, does not require extra cost and labor, such as exporting and analyzing data, which could allow teams to monitor athletes who have not been able to previously. Future research should investigate how the ACWR might not only be useful for injury prevention but also to aid in the improvement of an athlete's physiological state, as shown in this study.

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