

Comparisons Of Weekly Training Volumes Across A Season In Collegiate Female Lacrosse Athletes

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ABSTRACT

The purpose of this study was to describe the in-season variations of acute:chronic workload ratio (ACWR) of distance, high intensity distance (HID), sprints, accelerations, and decelerations between player positions of a Division I collegiate women's lacrosse team. Data were collected via wearable microtechnology across a total of 17 games and 64 training sessions on a total of 15 participants (attackers n=5, midfielders n=5, defenders n=5). ACWRs were calculated weekly by dividing the workload from the past seven days by the workload from the past 28 days for each metric. Two repeated measures analyses of variance (RM-ANOVA) were used to compare positional differences and weekly changes in all five metrics for 1) ACWR and 2) weekly training totals. There were several differences in weekly totals and ACWRs across all five metrics evaluated ($p < .05$), but no positional differences were noted. Apart from the early training weeks, ACWR primarily stayed within the optimal window of 0.8-1.5 to maximize performance and reduce injury risk. These data indicate that there is variation in weekly totals for the main five metrics studied that cause "spikes" and "valleys" in workload. However, the athletes had built enough of a base in their chronic workload that it did not affect their ACWR to move outside of the optimal window. Using this information, coaches and team physicians can more effectively program training not only to optimize performance, but also to limit injuries, fatigue, and lack of fitness.

Keywords: workload, athlete monitoring, physical fitness, team sport

INTRODUCTION

Monitoring athlete workload is a crucial part of managing an athlete's training to optimize performance while simultaneously reducing the risk of injuries. While progressive overload is necessary to push athletes and their physical capabilities, overtraining places athletes at higher risk for injuries, illness, and decreased performance.¹ The work performed by an athlete during training and competitions, also known as the external load, can be assessed using measurements such as speed, accelerations, and total distance covered during a session.² The rise in popularity of monitoring athlete load on an individual basis stems from the idea that fatigue is a multifactorial phenomenon that each athlete experiences differently and at various points of training. Therefore, as each athlete has unique stressors, genetic compositions, and conditions outside of training, and monitoring each athlete's individual stress response to training is key to maintaining healthy and fit athletes¹⁰⁻¹¹ and assisting with decision-making for return to play after an injury.¹²

The acute:chronic workload ratio (ACWR) is a model for analyzing athlete external load by providing insight on athlete preparedness and fitness. It is the relationship between acute training volumes during the previous seven days, and chronic training loads

for the last 3-6 weeks, with four weeks being common in sport science literature. The chronic load training periods should be selected to align with team training cycles when possible.^{1,4,6,8} The ACWR indicates an athlete's preparedness as it compares the load that the athlete has most recently performed directly to the amount of load that they have been prepared for.⁴ ACWR provides a method of objectively assessing an athlete's balance and progression in training. There are two ways to calculate ACWR: the rolling average model (RA) and the exponentially weighted moving average model (EWMA). The RA model is calculated by simply dividing the acute workload by the chronic workload. The EWMA model differs in determining the chronic workload as it prioritizes the most recent load performed by the athlete by assigning decreasing weighting for each older load value.⁵ While both methods of calculating ACWR are used, some studies have suggested that the EWMA model has a higher sensitivity for detecting increases of injury risk in athletes.⁶ Optimal ACWR (for both EWMA and RA) is within a range of 0.8-1.5; values under 0.8 indicate that an athlete may be undertrained, while values over 1.5 indicate overtraining.^{4,5} Values outside of this range or a large dip/spike in training puts athletes at a greater risk of injury.

While ACWR is a powerful monitoring tool, ACWR alone cannot be used as a predictive value for becoming injured.^{7,8} Recent literature has proposed that ACWR be dismissed as a model because the ratio creates an increased risk of artefacts that have no association with injury.⁷ While these arguments are noted, the present study did not use the ACWR in any relation to injuries. Rather, the value of using ACWR in athlete monitoring is that it addresses general principles of training such as individualization, variation, progression, and overload, and it can be used in combination with other measures when evaluating an athlete's performance and injury risk.⁹

A recent systematic review showcased 20 articles investigating ACWR and its association with non-contact injuries across Australian football, soccer, rugby, Gaelic football, hurling, cricket, American football, volleyball, and basketball. At the time, there were no studies on ACWR and injuries in female athletes.¹³ Since then, there has been only one study completed on ACWR in collegiate female athletes which found no association between RA and EWMA ACWR and injury in women's soccer.¹⁴ When evaluating and applying evidence-based practices in athlete monitoring and training, it is important to be cognizant of the fact that very little literature exists on

elite female athletes. This disparity in the literature² creates challenges to training female athletes as there is no comprehensive understanding of the current level of performance within female elite sport.¹⁵ Specific to athletic performance, physiological sex-based differences have been noted metabolically⁹ and in response to fatigue.³ Individuals respond to training differently, so applying practices and systems to female athletes that have only been studied in males is inherently problematic.

As each sport is unique in its physical and psychological demands, it is imperative that generalizations not be made across different sports. In the case of women's collegiate lacrosse, the literature is just now starting to characterize the demands of the sport. During a typical game of women's collegiate lacrosse, a study determined that players travel 4,733 meters with an average of 656 meters occurring at high-intensity speeds. This includes an average of 124 sprints, 6.1 high-intensity sprints, 51 high-intensity accelerations, and 38 high-intensity decelerations.¹⁶ Using this data, coaches can prepare athletes for high-intensity demands by curating pre-season and in-season training in a way that ensures sufficient fitness level and minimizes the risk of overtraining and overreaching. However, currently there is no literature that identifies a standardized monitoring tool. Most of the literature in women's lacrosse addresses injury rates, external load during games, energy status and body composition, and wellness.¹⁶⁻²⁰

The aforementioned studies suggest that while ACWR is not the sole predictor of non-contact injuries in professional sports, it is an effective monitoring tool for measuring an athlete's level of preparedness for training. However, most of the research regarding ACWR has focused on professional-level male sports. Currently, there is very limited research evaluating ACWR in women's sports, and the research on variations of ACWR between player positions in the sport of lacrosse is non-existent. The purpose of this study was to analyze the positional differences in external load and ACWR in weekly microcycles across a competitive season of a women's collegiate lacrosse team.

METHODS

Study Design

This was a prospective observational research study design. Data collection took place during the 2022

competitive season of National Collegiate Athletic Association Division I women's lacrosse. A total of 17 games and 64 training sessions were recorded. All athletes voluntarily participated in the study and were previously informed about the study design, risks and benefits, and implications. All participants completed written informed consent prior to study commencement. This study was conducted in accordance with the Declaration of Helsinki and approved by the university's Institutional Review Board.

Participants

Twenty-six female Division I collegiate lacrosse players were initially enrolled in this study. Eligibility criteria for this study included: 18 years of age or older, member of the varsity lacrosse team, and clearance to participate by the university's athletic trainers and team physician. Athletes were excluded from data analysis if participation was limited by injury ($n=2$) or they did not participate in at least 50% of the games ($n=9$). Using these criteria, a total of 15 participants (168.0 ± 5.8 cm, 66.3 ± 6.3 kg; attackers $n=5$, midfielders $n=5$, defenders $n=5$) were analyzed for this study.

Measures

External workload was quantified using VX Sport GPS units (Wellington, New Zealand). These units have been shown to be accurate and reliable methods of tracking workload.²¹⁻²² Metrics evaluated in this study included total distance in meters, high-intensity distance (HID) in meters, sprints (frequency), accelerations (frequency), and decelerations (frequency). HID was the distance that players ran at $>60\%$ of their maximum sprint speed (MSS). Sprints were the distance that players ran at $>80\%$ of their MSS. MSS was tested using previously established procedures.²¹ Accelerations and decelerations were quantified once there was a change in speed of greater than $3\text{m}\cdot\text{s}^{-2}$ detected. These metrics align with previous literature in women's lacrosse.²³⁻²⁴

The GPS units were turned on ten minutes prior to training sessions and games and connection with satellites was ensured prior to each session. Athletes wore the same unit for the whole season. Excess data from the sessions were trimmed using the VX Training Tool. Trimmed data included time spent prior to warm-up, water breaks, breaks in games, and time between the end of a session and when the units were turned off.

Weekly totals for each of the five metrics were tabulated for each athlete over the 15 weeks measured. RA ACWRs were calculated by dividing the acute workload (past 7 days) by the chronic workload (past 28 days). The ACWR for each of the five variables were calculated and recorded for the last training day of each week during the 2022 competitive season.

Statistical Analysis

Data analysis was performed using SPSS (version 27.0; IBM SPSS Inc., Chicago, IL, USA) and an alpha level of 0.05 was used to determine statistical importance. Data were categorized in weekly blocks comprising all training sessions and games. Descriptive statistics used to characterize the data were mean and standard deviation. A Shapiro-Wilk test was used to confirm normal distribution of results. Two repeated measures analyses of variance (RM-ANOVA) were used to compare by position (attackers, midfielders, and defenders) the 1) RA ACWRs for each metric and 2) the weekly totals for each metric. Univariate tests were used to interpret the main effects of the RM-ANOVAs, and paired t-tests were performed to analyze the differences for each metric by week. The weekly differences analysis only compared a week to its adjacent weeks (e.g., week 2 was compared to week 1 and 3 only). This analysis was chosen to focus on the weekly fluctuations in training volume, rather than comparisons in volume from early in the season to late in the season. Partial eta-squared (η^2) was calculated to determine the effect sizes. Effect sizes were interpreted as small (.01), moderate (.06), and large (.14).²⁵

RESULTS

Table 1 shows the number of training sessions and games per week during the season evaluated. The team was compliant with all NCAA regulations during the season. Figures 1-5 show the weekly totals between player positions in the histogram, and ACWR each week is expressed on the secondary axis with a line. For the weekly totals of each variable, there was no main effect for position ($\text{Lambda}(10,16)=1.073$, $p=.434$, $\eta^2=.401$). However, there was a main effect for week ($\text{Lambda}(70,784)=22.558$, $p<.001$, $\eta^2=.650$) and an interaction between position and week ($\text{Lambda}(140,815)=1.532$, $p<.001$, $\eta^2=.206$). Univariate analyses showed weekly differences for distance ($p<.001$, $\eta^2=.674$), HID ($p<.001$, $\eta^2=.702$), sprints ($p<.001$, $\eta^2=.880$), accelerations ($p<.001$,

$\eta^2=.700$), and decelerations ($p<.001$, $\eta^2=.696$). All effect sizes were considered large.

For RA ACWR, there was no main effect for position ($\text{Lambda}(10,18)=1.090$, $p=.418$, $\eta^2=.377$) or an interaction between week and position ($\text{Lambda}(140,884)=1.187$, $p=.082$, $\eta^2=.156$). There was a main effect for week ($\text{Lambda}(70,852)=33.386$, $p<.001$, $\eta^2=.716$). Univariate analyses showed weekly differences in RA ACWR for distance ($p<.001$, $\eta^2=.961$), HID ($p<.001$, $\eta^2=.918$), sprints ($p<.001$, $\eta^2=.908$), accelerations ($p<.001$, $\eta^2=.961$), and decelerations ($p<.001$, $\eta^2=.944$). All effect sizes were considered large.

Total distance

Figure 1 illustrates the weekly differences between player positions for the total weekly distance and distance ACWR. The paired t-tests showed differences in the total distance between week 1 and 2 ($t(23)=-10.779$, $p<.001$), week 3 and 4 ($t(23)=4.546$, $p<.001$), week 4 and 5 ($t(23)=4.357$, $p<.001$), week 5 and 6 ($t(24)=-3.420$, $p=.002$), week 6 and 7 ($t(24)=-4.093$, $p<.001$), week 7 and 8 ($t(22)=10.788$, $p<.001$), week 8 and 9 ($t(22)=-15.468$, $p<.001$), week 10 and 11 ($t(23)=2.337$, $p=.029$), and week 12 and 13 ($t(23)=3.982$, $p=.001$). The paired t-tests also showed differences in ACWR between week 1 and 2 ($t(23)=7.967$, $p<.001$), week 2 and 3 ($t(23)=15.638$, $p<.001$), week 3 and 4 ($t(23)=7.244$, $p<.001$), week 4 and 5 ($t(23)=2.531$, $p=.019$), week 6 and 7 ($t(24)=-2.614$, $p=.015$), week 7 and 8 ($t(24)=8.217$, $p<.001$),

week 8 and 9 ($t(24)=-6.953$, $p<.001$), week 10 and 11 ($t(23)=7.237$, $p<.001$), and week 12 and 13 ($t(23)=2.272$, $p=.033$). The lowest and highest mean distance value occurred during week 8 (15,379m) and week 9 (30,925m) respectively.

High-intensity distance

Figure 2 illustrates the weekly differences between player positions for the total weekly HID and HID ACWR. The paired t-tests showed differences in HID between week 1 and 2 ($t(19)=-7.179$, $p<.001$), week 2 and 3 ($t(23)=-3.635$, $p=.001$), week 3 and 4 ($t(23)=7.192$, $p<.001$), week 7 and 8 ($t(22)=5.174$, $p<.001$), week 8 and 9 ($t(22)=-9.581$, $p<.001$), week 9 and 10 ($t(23)=4.324$, $p<.001$), week 10 and 11 ($t(23)=5.218$, $p<.001$), week 12 and 13 ($t(21)=4.168$, $p<.001$), and week 14 and 15 ($t(19)=2.517$, $p=.021$). The paired t-tests also showed differences in the ACWR between weeks 1 and 2 ($t(20)=8.636$, $p<.001$), week 2 and 3 ($t(23)=11.287$, $p<.001$), week 3 and 4 ($t(23)=9.370$, $p<.001$), week 7 and 8 ($t(24)=2.239$, $p=.035$), week 8 and 9 ($t(23)=-6.570$, $p<.001$), week 9 and 10 ($t(23)=3.643$, $p=.001$), week 10 and 11 ($t(23)=6.422$, $p<.001$), and week 13 and 14 ($t(19)=-2.341$, $p=.030$). The lowest weekly mean occurred during week 15 (1,271 m) and the highest mean occurred during week 3 (3,753 m). There was a spike in ACWR across all positions in week 9 with an RA ACWR mean of 1.41 between all positions. In week 12, attackers specifically saw an increase in ACWR to 1.07 from 0.714 in week 11.

Table 1. Distribution of training sessions and games for each week analyzed.

Week	Number of Training Sessions	Number of Games
1	4	0
2	6	0
3	5	1
4	6	1
5	5	0
6	6	1
7	6	1
8	2	1
9	5	1
10	5	1
11	4	2
12	4	2
13	4	2
14	4	2
15	4	2

Sprint efforts

Figure 3 illustrates the weekly differences between player positions for the total weekly sprint effort averages and sprint ACWR. The paired t-tests showed differences in the sprints between week 1 and 2 ($t(19)=-6.295$, $p<.001$), week 2 and 3 ($t(23)=-14.824$, $p<.001$), week 3 and 4 ($t(23)=13.137$, $p<.001$), week 4 and 5 ($t(23)=2.901$, $p=.008$), week 7 and 8 ($t(22)=3.969$, $p=.001$), week 8 and 9 ($t(22)=-7.861$, $p<.001$), week 9 and 10 ($t(23)=4.368$, $p<.001$), week 10 and 11 ($t(23)=4.059$, $p<.001$), week 12 and 13 ($t(21)=3.590$, $p=.002$). The paired t-tests also showed differences in the ACWR between weeks 1 and 2 ($t(20)=9.618$, $p<.001$), week 3 and 4 ($t(23)=17.996$, $p<.001$), week 4 and 5 ($t(23)=2.391$, $p=.025$), week 5 and 6 ($t(24)=-3.615$, $p=.001$), week 8 and 9 ($t(23)=-6.606$, $p<.001$), week 9 and 10 ($t(23)=3.770$, $p=.001$), week 10 and 11 ($t(23)=5.934$, $p<.001$), and week 11 and 12 ($t(22)=-2.598$, $p=.016$). The highest weekly means occurred during week 3 with 116 sprint efforts. This was an increase from week 2 with 40 sprint efforts. This resulted in a RA ACWR of 1.87 for the team in week 3. This is the only metric where there was an increase in ACWR in week 3 as opposed to a steady decrease like in the other metrics. ACWR was also higher in week 9 with a total average of 1.48.

Accelerations

Figure 4 illustrates the weekly differences between player positions for the total weekly accelerations and acceleration ACWR. The paired t-tests showed differences in accelerations between week 1 and 2 ($t(21)=-8.926$, $p<.001$), week 3 and 4 ($t(23)=12.409$, $p<.001$), week 5 and 6 ($t(24)=-2.200$, $p=.038$), week 6 and 7 ($t(24)=-5.537$, $p<.001$), week 7 and 8 ($t(22)=10.841$, $p<.001$), week 8 and 9 ($t(22)=-12.176$, $p<.001$), week 9 and 10 ($t(23)=2.521$, $p=.010$), week 10 and 11 ($t(23)=4.140$, $p<.001$), and week 12 and 13 ($t(21)=3.379$, $p=.003$). The paired t-tests also showed differences in the ACWR between weeks 1 and 2 ($t(21)=10.713$, $p<.001$), week 2 and 3 ($t(23)=15.438$, $p<.001$), week 3 and 4 ($t(23)=9.070$, $p<.001$), week 6 and 7 ($t(24)=2.368$, $p=.026$), week 7 and 8 ($t(24)=8.993$, $p<.001$), week 8 and 9 ($t(23)=9.579$, $p<.001$), and week 10 and 11 ($t(23)=7.264$, $p<.001$). The lowest acceleration efforts occurred during week 8 (265) and the highest occurred during week 3 (590). There was an increase in total number of accelerations and ACWR in week 9 with a total ACWR of 1.27 after a total of 0.74 in week 8.

Decelerations

Figure 5 illustrates the total weekly decelerations and deceleration ACWR. The paired t-tests showed

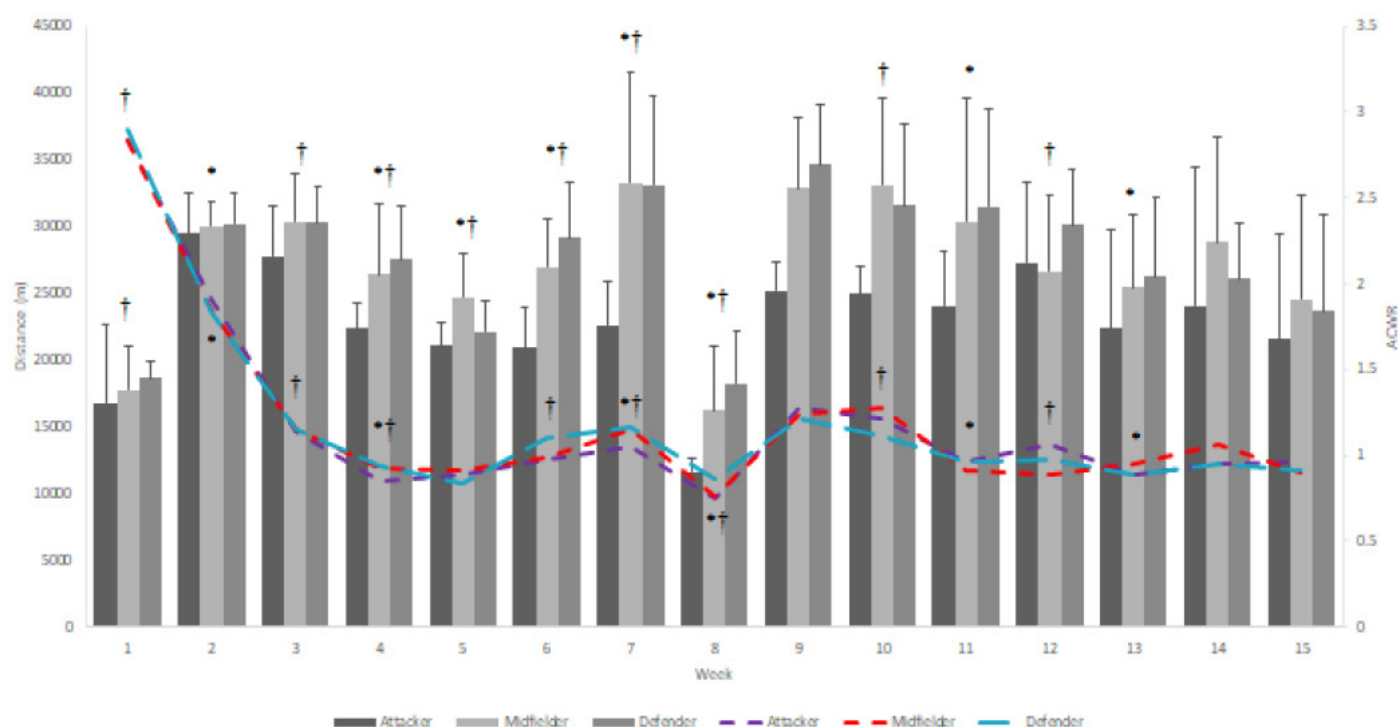


Figure 1. Mean weekly totals of distance for each position are shown in the column bars and mean ACWR for each position is shown via the lines that are affiliated with the secondary y-axis. * indicates a difference from the previous week and † indicates a difference from the subsequent week, $p<.05$.

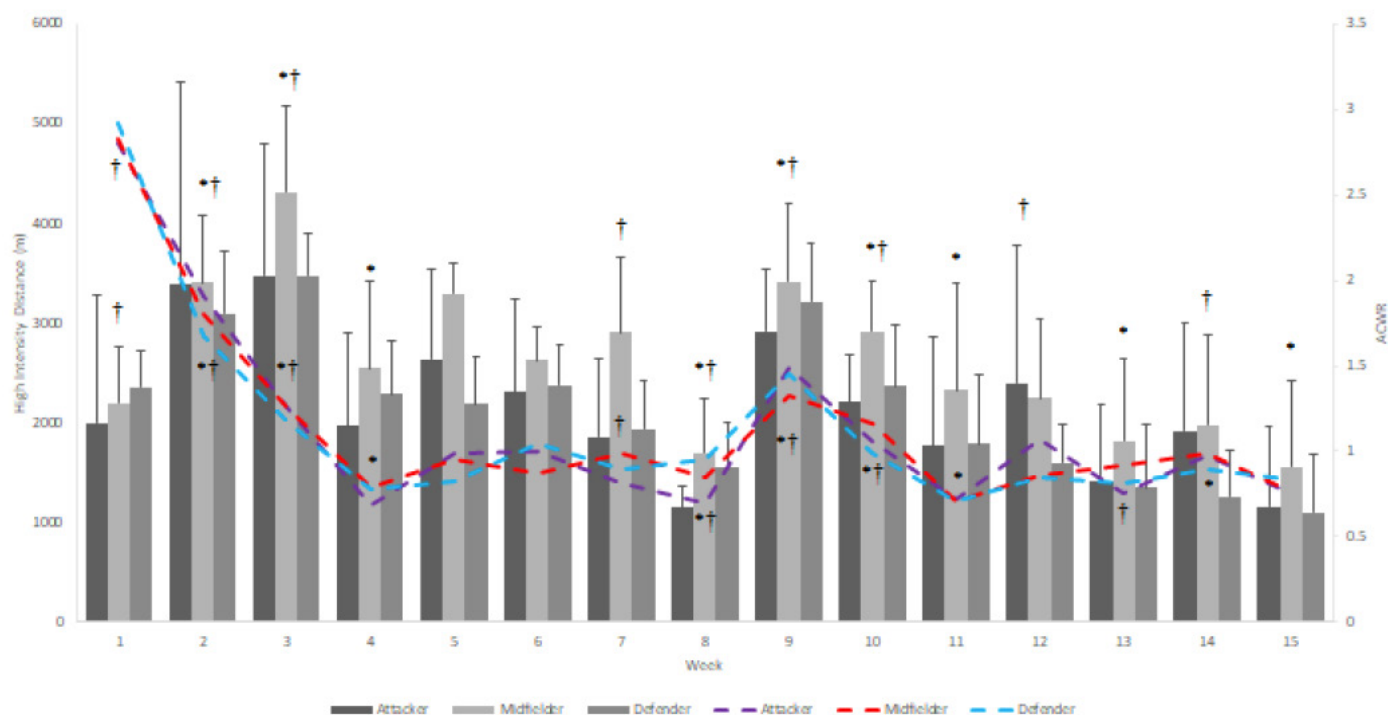


Figure 2. Mean weekly totals of High Intensity Distance for each position are shown in the column bars and mean ACWR for each position is shown via the lines that are affiliated with the secondary y-axis. * indicates a difference from the previous week and † indicates a difference from the subsequent week, $p < .05$.

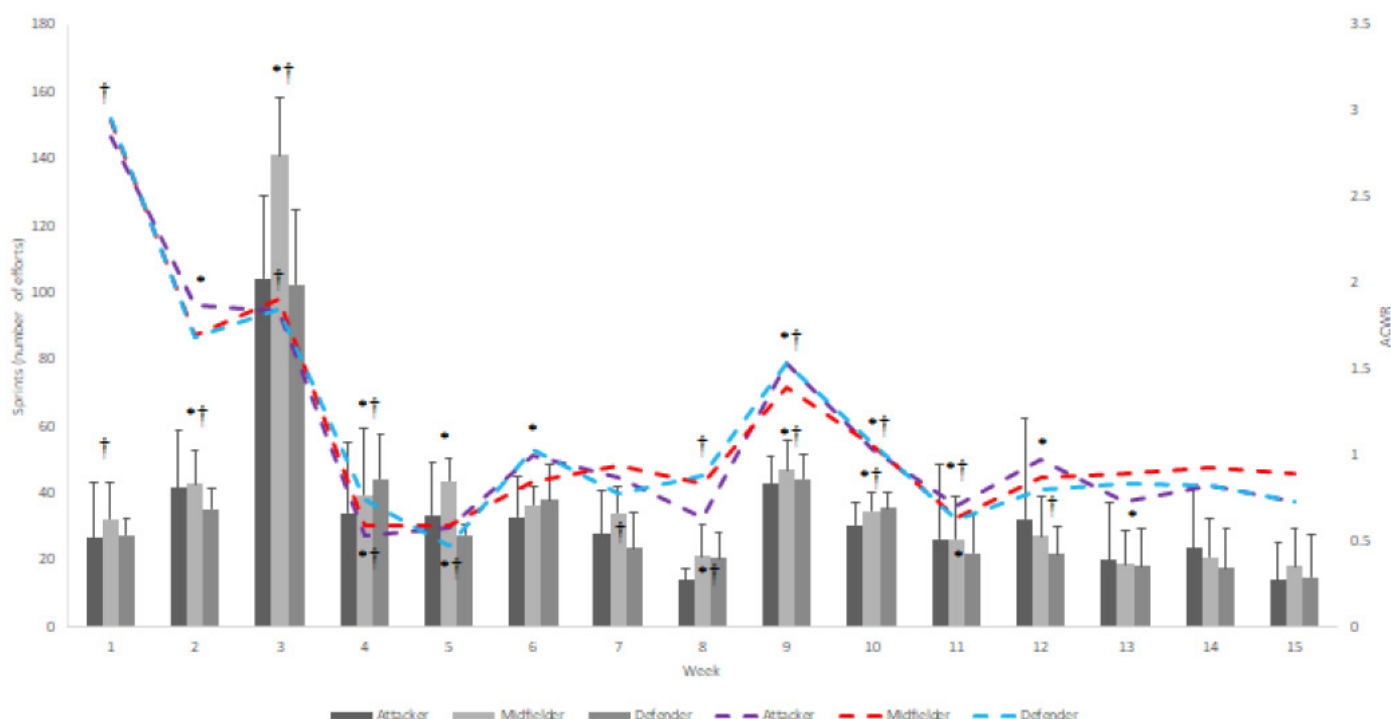


Figure 3. Mean weekly totals of sprint efforts for each position are shown in the column bars and mean ACWR for each position is shown via the lines that are affiliated with the secondary y-axis. * indicates a difference from the previous week and † indicates a difference from the subsequent week, $p < .05$.

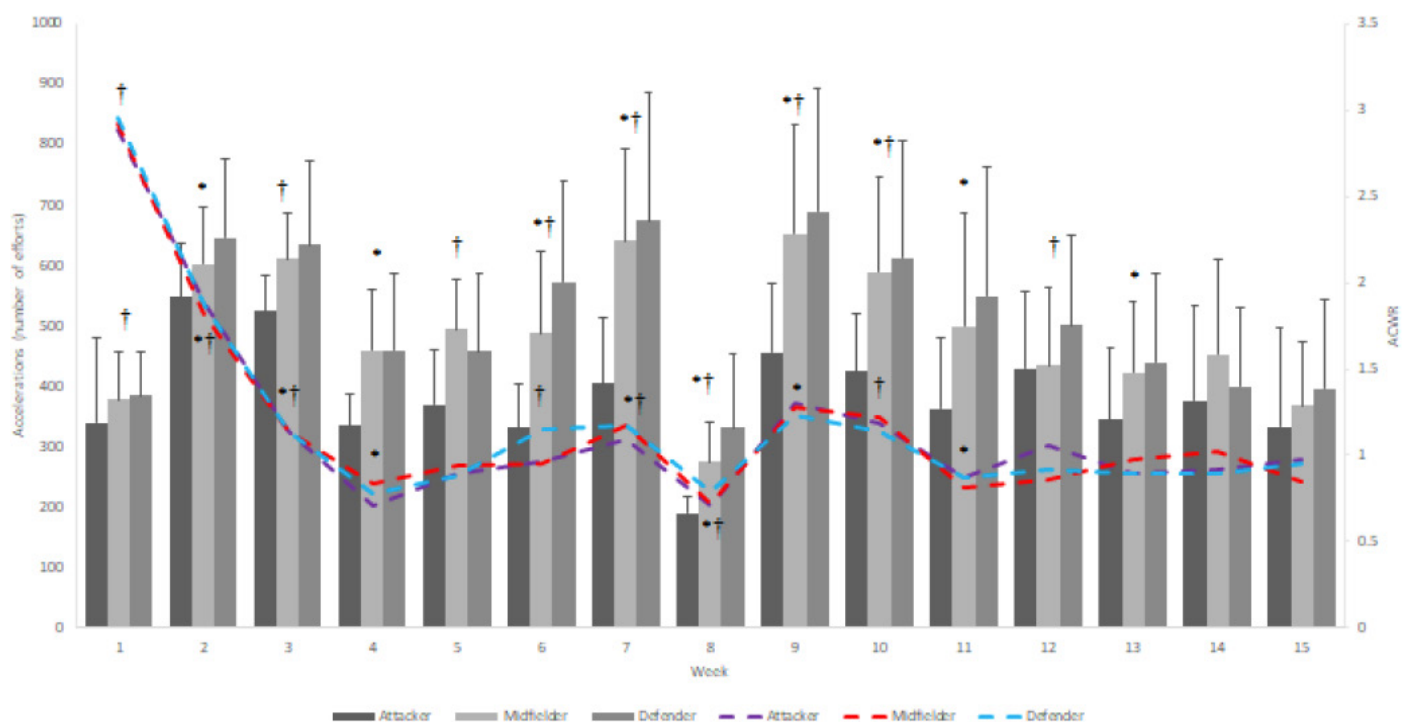


Figure 4. Mean weekly totals of accelerations for each position are shown in the column bars and mean ACWR for each position is shown via the lines that are affiliated with the secondary y-axis. * indicates a difference from the previous week and † indicates a difference from the subsequent week, $p < .05$.

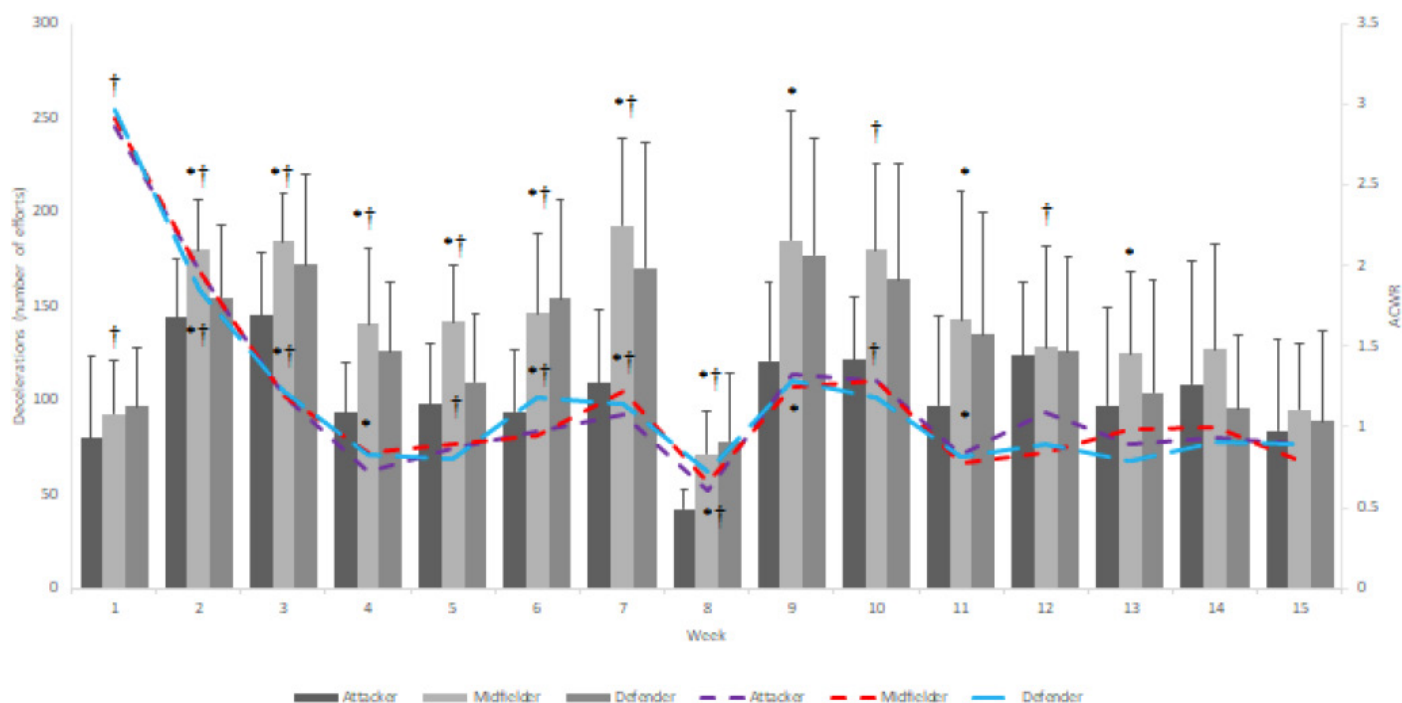


Figure 5. Mean weekly totals of decelerations for each position are shown in the column bars and mean ACWR for each position is shown via the lines that are affiliated with the secondary y-axis. * indicates a difference from the previous week and † indicates a difference from the subsequent week, $p < .05$.

differences in the total decelerations between week 1 and 2 ($t(19)=-14.143$, $p<.001$), week 2 and 3 ($t(23)=-2.440$, $p=.023$), week 3 and 4 ($t(23)=6.918$, $p<.001$), week 4 and 5 ($t(23)=2.224$, $p=.036$), week 5 and 6 ($t(24)=-2.950$, $p=.007$), week 6 and 7 ($t(24)=-4.397$, $p<.001$), week 7 and 8 ($t(22)=10.298$, $p<.001$), week 8 and 9 ($t(22)=-9.492$, $p<.001$), week 10 and 11 ($t(23)=5.528$, $p<.001$), and week 12 and 13 ($t(21)=3.591$, $p=.002$). The paired t-tests also showed differences in deceleration ACWR between weeks 1 and 2 ($t(19)=14.999$, $p<.001$), weeks 2 and 3 ($t(23)=15.043$, $p<.001$), weeks 3 and 4 ($t(23)=10.040$, $p<.001$), weeks 5 and 6 ($t(24)=-2.106$, $p=.046$), weeks 6 and 7 ($t(24)=-2.118$, $p=.045$), weeks 7 and 8 ($t(24)=8.557$, $p<.001$), weeks 8 and 9 ($t(23)=-7.558$, $p<.001$), and week 10 and 11 ($t(23)=8.676$, $p<.001$). The lowest decelerations occurred during week 8 (64) and the highest occurred during week 3 (167). These decelerations doubled from week 8 to week 9, and as a result the ACWR in week 9 was 1.29.

DISCUSSION

This study describes the in-season variations of ACWR and external workload between positions on a Division I collegiate women's lacrosse team. Our findings showed variations in total weekly workload and ACWR between weeks, but no differences by position. This implies variation in weekly workload for all players, which justifies the need for detailed training load monitoring, such as ACWR, in this population.

As anticipated, ACWR was high early in the season as the chronic workload base was built. After a 28-day base was established, ACWR primarily stayed within the "optimal" range for all five variables evaluated, with a few exceptions. A decrease below 0.8 in ACWR was noted for all five variables in weeks 4 and 8. The drop in ACWR in week 4 was likely mathematical in nature as there was a full 28 days of chronic workload available. Whereas the drop in ACWR at week 8 was due to very low overall training volume that week with only two training sessions and one game. This de-load week was in between two high volume weeks. This may have helped the athletes recover from week 7 during week 8, and therefore tolerate the demand of week 9 better. It was found that the sprint efforts were the least adherent to the optimal training zone of an ACWR. Weeks 3 and 9 were the most physically demanding in sprints, resulting in ACWRs >1.5 . Sprints in week 3 were more than double that of any other week, with a

higher demand in midfielders. The purpose in higher sprints in week 3 was to help build the high-intensity base for the athletes, but the training was likely more than originally intended. The increase in ACWR in week 9 was related to the de-load of week 8, causing a subsequent spike in ACWR. Other than during the initial two weeks of the season, no positions exhibited a spike over 1.5 across the remainder of the season for acceleration and deceleration efforts ACWR. HID and sprints were primarily front-loaded to have higher demand early in the season and then taper off as the season progressed. Both ACWR and weekly total data demonstrated extreme variance throughout the season for each variable. The fluctuations should be further investigated to analyze why these "spikes" and "valleys" are occurring and whether they are impacting athlete performance. Sprints had the most ACWR values indicating undertraining, so further investigation into the workload and demand of this variable is warranted.

Coaches of the team in the present study created weekly goals for each external load variable and monitored workloads daily. Setting these goals ahead of time likely helped the ACWRs stay within optimal ranges. Additionally, the final five weeks of the season consisted of conference play with a consistent schedule of two games per week. External workloads were primarily maintained or showed slight declines during this time. This was likely a result from the consistent schedule, changes in training due to travel, and intentional declines in training demands to meet the increased game demand during the peak period of the season. Coaches and sport scientists evaluating external workload should examine their data through the lenses of daily, weekly, and monthly totals to understand the compounding effects of the training and game play.

This study demonstrated that attackers, midfielders, and defenders had virtually no differences in workload demands across the season. This finding contrasts other studies that analyzed and support position-specific training in women's lacrosse.²⁶⁻²⁸ In the international women's game, defenders logged less total distance, attackers logged more distance in spring speed zone 1 and less distance in sprint speed zone 2.²⁶ Bynum et al. showed that attackers logged more total distance and metabolic equivalent distance than midfielders, but midfielders had more decelerations and faster speed during games.²⁸ Results from the present study may contrast that of previous literature based on differing styles of play, substitution strategies, and level of competition. In

future research, it may be useful to evaluate workload per minute of time played when making positional comparisons. Using this information, coaches can optimize weekly training sessions per position, and potentially limit injuries, fatigue, and lack of fitness. While the purpose of this study was not to correlate or predict injury rates based on ACWR values outside of the optimal training range, the fact that there were numerous weeks and metrics that indicated under/overtraining must be acknowledged.

Overtraining does not only negatively impact an athlete's physical and mental health, but it is also prohibited by the National Collegiate Athletic Association (NCAA). According to the NCAA's operating bylaws, student-athlete participation is limited to 20 hours/week during in-season and eight hours/week during the off-season.²⁹ Other than the time specifically dedicated to their physical sport, student athletes have other responsibilities such as media activities, fundraising, and traveling to and from competitions, that they must balance along with being a full-time student. In order to remain cognizant of the amount of work that student-athletes are putting into their sport, it is important that coaches continue to use tools such as ACWR to monitor their athletes workload and ensure that they are not being overtrained. Additionally, studies have even shown that strategic decreases in training volume over the span of two weeks, also known as tapering, maximizes performance.³⁰

This study has a few methodological limitations that should be acknowledged. First, the sample size was low, as only one team was analyzed during one season. Second, this study only included external load variables and no subjective data from the athletes. Ratings of perceived exertion provide a more holistic view of the physiological responses to load and fatigue in players. Data regarding pain, injuries, and missed training sessions were also not collected. Future research should include evaluating the changes in objective external workload in conjunction with subjective assessments of internal workload and wellness to provide a more holistic view of the athletes' experiences throughout a season. Finally, the findings of this study are specific to collegiate female lacrosse players. While it is one of the first studies to analyze ACWR in this population, more studies should be done to analyze female athletes across other sports and other ages. In summary, this study provides detailed information about the variations in total weekly distance, HID, sprints, accelerations, decelerations, and ACWR across different positions in one season of women's

collegiate lacrosse. Using this information, coaches, athletic trainers, and team physicians should consider the variations of training load and player's individual responses to load to prevent overtraining and optimize player and team performance. Using the concepts of periodization and individualization, coaches of different positions can further tailor their training and recovery periods in accordance to their own physical requirements.

REFERENCES

1. Load, overload, and recovery in the athlete. *Current Sports Medicine Reports*. 2019;18(4):141-148. doi:10.1249/jsr.0000000000000589
2. Bourdon PC, Cardinale M, Murray A, et al. Monitoring athlete training loads: Consensus statement. *International Journal of Sports Physiology and Performance*. 2017;12(s2):S2-161S2-170. doi:10.1123/ijsp.2017-0208
3. Impellizzeri FM, Marcora SM, Coutts AJ. Internal and external training load: 15 years on. *International Journal of Sports Physiology and Performance*. 2019;14(2):270-273. doi:10.1123/ijsp.2018-0935
4. Gabbett TJ. The training—injury prevention paradox: Should athletes be training smarter and harder? *British Journal of Sports Medicine*. 2016;50(5):273-280. doi:10.1136/bjsports-2015-095788
5. Williams S, West S, Cross MJ, Stokes KA. Better way to determine the acute:chronic workload ratio? *British Journal of Sports Medicine*. 2016;51(3):209-210. doi:10.1136/bjsports-2016-096589
6. Murray NB, Gabbett TJ, Townshend AD, Blanch P. Calculating acute:chronic workload ratios using exponentially weighted moving averages provides a more sensitive indicator of injury likelihood than rolling averages. *British Journal of Sports Medicine*. 2016;51(9):749-754. doi:10.1136/bjsports-2016-097152
7. Fanchini M, Rampinini E, Riggio M, Coutts AJ, Pecci C, McCall A. Despite association, the acute:chronic work load ratio does not predict non-contact injury in elite footballers. *Science and Medicine in Football*. 2018;2(2):108-114. doi:10.1080/24733938.2018.1429014
8. Impellizzeri FM, Wookcock S, Coutts AJ, Fanchini M, McCall A, Vigotsky AD. Acute to random workload ratio is "as" associated with injury as acute to actual chronic workload ratio: Time to dismiss ACWR and its components. *SportRxiv*. 2020. doi:10.31236/osf.io/e8kt4
9. Gabbett TJ. How much? How fast? How soon? Three simple concepts for progressing training loads to minimize injury risk and enhance performance. *Journal of Orthopaedic & Sports Physical Therapy*. 2019;50(10):1-9. doi:10.2519/jospt.2020.9256
10. Noakes TD. Fatigue is a brain-derived emotion that regulates the exercise behavior to ensure the

- protection of whole body homeostasis. *Frontiers in Physiology*. 2012;3. doi:10.3389/fphys.2012.00082
11. Mann TN, Lamberts RP, Lambert MI. High responders and low responders: Factors associated with individual variation in response to standardized training. *Sports Medicine*. 2014;44(8):1113-1124. doi:10.1007/s40279-014-0197-3
 12. Kupperman N, DeJong AF, Alston P, Hertel J, Saliba SA. Athlete workloads during collegiate women's soccer practice: Implications for return-to-play. *Journal of Athletic Training*. 2021;56(3):321-330. doi:10.4085/205-20
 13. Griffin A, Kenny IC, Comyns TM, Lyons M. The association between the acute:chronic workload ratio and injury and its application in team sports: A systematic review. *Sports Medicine*. 2020;50(3):561-580. doi:10.1007/s40279-019-01218-2
 14. Xiao M, Nguyen JN, Hwang CE, Abrams GD. Increased lower extremity injury risk associated with player load and distance in collegiate women's soccer. *Orthopaedic Journal of Sports Medicine*. 2021;9(10):232596712110482. doi:10.1177/23259671211048248
 15. Emmonds S, Heyward O, Jones B. The challenge of applying and undertaking research in female sport. *Sports Medicine - Open*. 2019;5(1). doi:10.1186/s40798-019-0224-x
 16. Devine NF, Hegedus EJ, Nguyen AD, Ford KR, Taylor JB. External match load in women's collegiate lacrosse. *Journal of Strength and Conditioning Research*. 2022;36(2):503-507. doi:10.1519/jsc.0000000000003451
 17. Barber Foss KD, Le Cara E, McCambridge T, Hinton RY, Kushner A, Myer GD. Epidemiology of injuries in women's lacrosse. *Clinical Journal of Sport Medicine*. 2018;28(4):406-413. doi:10.1097/jsm.0000000000000458
 18. Zabriskie H, Currier B, Harty P, Stecker R, Jagim A, Kerksick C. Energy status and body composition across a collegiate women's lacrosse season. *Nutrients*. 2019;11(2):470. doi:10.3390/nu11020470
 19. Crouch AK, Jiroutek MR, Snarr RL, Bunn JA. Relationship between pre-training wellness scores and internal and external training loads in a Division I women's lacrosse team. *Journal of Sports Sciences*. 2021;39(9):1070-1076. doi:10.1080/02640414.2020.1857106
 20. Frick M, Hamlet M, Tudini F, Bunn J. No correlation between wellness and countermovement jump in female collegiate lacrosse players. *Journal of Australian Strength & Conditioning*. 2021;29(4):28-34.
 21. Alphin KL, Sisson OM, Hudgins BL, Noonan CD, Bunn JA. Accuracy assessment of a GPS device for maximum sprint speed. *International Journal of Exercise Science*. 2020;13(4):273-280.
 22. Malone S, Doran D, Collins K, Morton JP, McRoberts A. Accuracy and reliability of the VXSport global positioning system in intermittent activity. In: *Proceedings of the 19th Annual Congress for the European College of Sport Science*, 2-5th July, Amsterdam, Netherlands 2014
 23. Bunn JA, Myers BJ, Reagor MK. An evaluation of training load measures for drills in women's collegiate lacrosse. *International Journal of Sports Physiology and Performance*. 2020;1-8. doi:10.1123/ijspp.2020-0029
 24. Bunn J, Myers B, Reagor M. An evaluation of internal and external workload metrics in games in women's collegiate lacrosse. *The Journal of Sport and Exercise Science*. 2022;6(1). doi:10.36905/jses.2022.01.02
 25. Cohen J. *Statistical Power Analysis for the Behavioural Science (2nd Edition)*. Statistical Power Analysis for the Behavioral Sciences. 1988.
 26. Hauer R, Tessitore A, Hauer K, Tschan H. Activity profile of international female lacrosse players. *Journal of Strength and Conditioning Research*. 2021;35(11):3207-3212. doi:10.1519/JSC.0000000000003253
 27. Hoffman JR, Ratamess NA, Neese KL, et al. Physical performance characteristics in National Collegiate Athletic Association Division III champion female lacrosse athletes. *J Strength Cond Res*. 2009;23(5):1524-1529. doi:10.1519/JSC.0b013e3181b3391d
 28. Bynum L, Snarr RL, Myers BJ, Bunn JA. Assessment of relationships between external load metrics and game performance in women's lacrosse. *International Journal of Exercise Science*. 2022;15(6):488-497.
 29. 2022-2023 NCAA Division I Manual.; 2022. <https://www.ncaapublications.com/p-4657-2022-2023-ncaa-division-i-manual.aspx>
 30. Bosquet L, Montpetit J, Arvisais D, Mujika I. Effects of tapering on performance: a meta-analysis. *Medicine and Science in Sports and Exercise*. 2007;39(8):1358-1365. doi:10.1249/mss.0b013e31806010e0