

## **An evaluation of internal and external workload metrics in games in women's collegiate lacrosse**

Jennifer A. Bunn<sup>1\*</sup>, Mary Reagor<sup>2</sup>, Bradley J. Myers<sup>3</sup>

<sup>1</sup>*Department of Kinesiology, Sam Houston State University, USA*

<sup>2</sup>*Independent consultant, USA*

<sup>3</sup>*Department of Physical Therapy, Campbell University, USA*

---

### ARTICLE INFO

*Received: 06.05.2021*

*Accepted: 27.09.2021*

*Online: 24.03.2022*

---

### Keywords:

*TRIMP*

*Heart rate*

*High-intensity distance*

*Sprint*

*Athlete monitoring*

---

### ABSTRACT

*The purpose of this study was to statistically evaluate internal and external workload metrics in women's collegiate lacrosse games. Twelve Division I collegiate female lacrosse players wore a heart rate (HR) monitor and microtechnology during 17 intercollegiate games. Seven measures were used to determine game workload: two internal measures (mean HR and training impulse [TRIMP]) and five external measures (total distance, high-intensity distance [HID], average speed, accelerations, and decelerations). Principal component analysis (PCA) was used to determine which metrics were most associated with each game segment. A permutation test validated the number of components retained for each PCA, and a bootstrap ratio test validated which measures significantly loaded on each component. For the whole game and each half all variables significantly loaded as factors onto only one principal component. For the whole game, the workload variables explained 54% of the variance ( $p < .001$ ). The same metrics explained 53% of the variance for the first half ( $p < .001$ ), and 58% of the variance for the second half ( $p < .001$ ). External workload measures were highly intercorrelated and internal measures provided less information to the structure across all three PCAs analyzed. Analyses showed similar factor-loading patterns for the three PCAs indicating very little difference in importance of workload variables by game section. The loaded metrics should be compared to a complementary analysis for drills to ensure that training workload metrics are similar.*

---

### 1. Introduction

The use of global positioning systems (GPS) microtechnology and heart rate (HR) monitors have simplified and improved training load monitoring in athletes from various sports. The outputs from these devices and software systems are vast, and allow for specific measures of external training load (e.g., total distance, high-intensity distance, sprints, accelerations, decelerations, sprint speed zones, metabolic equivalent distance, player/athlete load) and internal training load (e.g., maximum HR, average HR, training impulse [TRIMP], and ratings of perceived exertion [RPE]). Previous literature has evaluated similar data for a variety of elite male athletes playing rugby (Weaving et al., 2014; Weaving et al., 2017) and football (Akenhead & Nassis, 2016),

and a meta-analysis (McLaren et al., 2018) was conducted with various sports including: Australian Rules football, soccer, and basketball. Typical analyses include principal component analysis (PCA) to evaluate factor loadings, importance of the metrics, and redundancy between metrics. PCA is a method of variable reduction and has been used in sport science to evaluate the number of variables necessary to explain workload (Bunn et al., 2021; Weaving et al., 2014, 2019; Weaving et al., 2017). These studies have helped shed light on the most important external and internal metrics to evaluate within each specific sport, which helps sport scientists monitor training load and coaches conduct training sessions to be more game-specific (Akenhead & Nassis, 2016; McLaren et al., 2018; Vanrenterghem et al., 2017; Weaving et al., 2014; Weaving et al., 2017). Steps for sport scientists to mimic

---

\*Corresponding Author: Jennifer A. Bunn, Department of Kinesiology, Sam Houston State University, USA, [jab229@SHSU.EDU](mailto:jab229@SHSU.EDU)

the analyses with their own data have also been published (Weaving et al., 2019). Overall, much of this literature has shown that workload in these sports are often best evaluated using both internal and external load variables. PCA outcomes typically show internal and external metrics associated with different components suggesting they are not redundant measures. While these data are useful, they likely have little cross-over into women's athletics or sports different from what have previously been analyzed.

Lacrosse is a rapidly growing sport in men's and women's athletics with a steady increase in the number of players in youth and collegiate leagues (National Collegiate Athletic Association® Sports Sponsorship and Participation Rates, 2019). This is accompanied by an increasing number of publications evaluating player profiles and game and training load statistics (Akiyama et al., 2019; Alphin et al., 2019; Devine et al., 2020; Hauer et al., 2019; Polley et al., 2015). The men's and women's games have different rules with restraining line implementations, play time is constructed in quarters in men's games and in halves for women, and there is reduced contact in the women's game, which results in different game and training load profiles for these athletes. Available literature allows game profile comparisons between elite male athletes (Akiyama et al., 2019) and collegiate female athletes (Devine et al., 2020). Men and women tend to cover similar total distances during match play, apart from male midfielders moving less total distance than female midfielders. Male lacrosse athletes logged higher distances at high speeds than female athletes, and more accelerations and decelerations.

While it is important to know and understand the game and training profiles of lacrosse athletes, the literature has yet to determine which internal and external metrics are most important for evaluation. Bunn et al. (2021) recently evaluated the load metrics of different drill types during four months of pre-season training in women's collegiate lacrosse. The PCA showed that internal and external workload metrics loaded similarly between different drill types, and all drill types emphasized a greater importance for external metrics, as they loaded onto the first component, and a secondary emphasis on the internal metrics which loaded on the second component. This provides important information for sport scientists and coaches to guide training, but there is no evidence regarding how this information compares to their competitive games. The primary purpose of the present study was to statistically evaluate the relationship of internal and external workload metrics in women's collegiate lacrosse games. Comparing the results of game data in the present study with training data from previous literature (Bunn et al., 2021) will provide coaches and sport scientists greater clarity in understanding important variables for measuring workload and a concept of training modes that translate best to game style of play. A secondary purpose was to evaluate workload differences between the first and second halves of women's collegiate lacrosse.

## 2. Methods

### 2.1. Participants

Twenty-five female Division I collegiate lacrosse players were enrolled in this study, but data from only 12 key players ( $19.9 \pm$

$1.1$  years,  $166.4 \pm 5.4$  cm,  $64.5 \pm 5.4$  kg) were utilized. These individuals were identified as key players by their coaches based upon minutes played and team contribution. Eligibility criteria for study participation included: 18 years of age or older, member of the varsity roster, clearance for full participation provided by a certified athletic trainer and team physician and contributing to at least 50% of the game minutes played. Athletes were excluded if participation was limited by injury or if they contributed to fewer than 50% of the game minutes played. These criteria were set up to exclude players who did not play much and spent much of the game time on the sideline. This study was conducted in accordance to the Declaration of Helsinki and approved by the Campbell University Institutional Review Board. All participants completed written informed consent prior to all data collection.

### 2.2. Design

This was a longitudinal observational research study design. Data collection took place during a three-month competitive season of National Collegiate Athletic Association (NCAA) Division I women's lacrosse play. A total of 17 games were recorded, resulting in 200 total observations, averaging  $16.7 \pm 0.7$  games per player.

### 2.3. Procedure

Training load metrics were collected using VX Sport microtechnology units and HR monitors (Wellington, New Zealand). The GPS microtechnology unit sampled at 10 Hz and included a tri-axial accelerometer, tri-axial magnetometer, and tri-axial gyroscope. This unit has been shown to have an acceptable level of accuracy and reliability (Alphin et al., 2020; Malone et al., 2014).

Seven total metrics were evaluated in this study – two internal and five external. The internal load metrics included average HR expressed as beats per minute (bpm), and training impulse (TRIMP) expressed in arbitrary units (AU). The external load metrics included total distance in meters, high-intensity distance (HID) in meters, average speed in  $\text{m}\cdot\text{min}^{-1}$ , decelerations (frequency), and accelerations (frequency). HID was the distance run at greater than 60% of maximum sprint speed. Accelerations and decelerations were counted when there was a change in acceleration of greater than  $7 \text{ m}\cdot\text{s}^{-2}$ . These metrics were chosen to align with previous work with elite male rugby athletes (Weaving et al., 2014; Weaving et al., 2017), and previous literature in collegiate women's lacrosse (Alphin et al., 2019; Bunn et al., 2021; Devine et al., 2020). Explanations of each metric and methods for measurement were previously provided by Bunn et al. (2021).

GPS units and HR monitors were distributed to participants prior to each game. Players utilized the same unit and monitor for each game. Units and monitors were collected at the end of each game for upload and data trimming and splitting. Inactive times were removed from the data, and games were split according to warm-up, first half, and second half. Only the first half, second half, and whole game data were analyzed. Time spent in warm-up, half-time, and cool down were trimmed out of the data.

2.4. Statistical Approach

For the primary aim of this study, PCA was used to determine which of the seven measures were most associated with load in the first and second halves and whole game data. PCA takes the set of observed variables, which are possibly correlated, and converts them into a set of linearly uncorrelated variables called principal components (Abdi & Williams, 2010). Seven measures were taken to determine load: the two internal measures included average HR and TRIMP, and the five external measures included total distance, average speed, HID, accelerations, and decelerations. The number of principal components in a PCA is equal to the number of input variables, but few of these are likely to be useful. Therefore, a permutation test with 5000 iterations was used to validate the number of components that were retained for each PCA. Permutation tests have been shown to be more reliable than other stopping rules when the population distribution is not known, the variables are correlated or the sample size is small (Devine et al., 2020; Hauer et al., 2019), as with the present data. Additionally, because the sample distribution was unknown, a bootstrap ratio test was used to validate which measures significantly loaded on each component. A bootstrap ratio test is significant when the contribution of the variables is consistent across the bootstrap samples. Thus, the bootstrap was used to determine the stability of the contribution of each of the variables to each component (Beaton et al., 2014). An alpha threshold of .05 was used to determine significance. PCA and subsequent analyses

were done in R (R Core Team, 2013) using the InPosition statistical inference package.

Means and standard deviations for all key players were calculated for the first half, second half, and whole game. Differences between first and second half internal and external load variables were evaluated using paired samples t-tests to evaluate the secondary aim of the present study. Cohen's d effect sizes were calculated to determine the magnitude of differences between halves. Interpretation of effect sizes were small (0.2 – 0.49), moderate (0.50-0.79) and large ( $\geq 0.80$ ) (Cohen, 1988). These data were analyzed using jamovi (The jamovi project, 2020).

3. Results

Figure 1 shows the results of the PCA for the first half (A), second half (B), and whole game (C). Each analysis extracted only one significant principal component, and all variables loaded significantly on the first component. For the first half, all loaded variables accounted for 52.8% ( $p < .01$ ) of the variance. In the second half, the variables explained 57.9% ( $p < .01$ ) of the variance. Finally, for the whole game, the variables explained 53.6% ( $p < .01$ ) of the variance.

Table 1 shows the factor scores, bootstrap ratios, and loadings for each principal component for each aspect of the game analyzed. As previously stated, all variables loaded onto the first component for the first and second halves and the whole game.

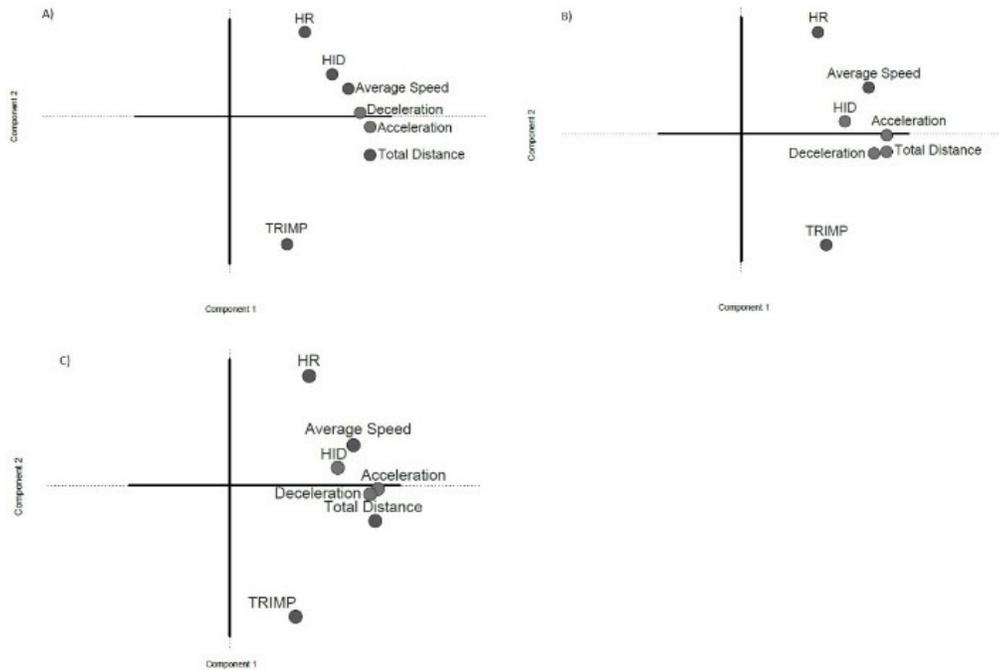


Figure 1: Results of the PCA for each component of the games analyzed, A) First half, component 1 contained 52.8% of the variance,  $p < .01$ , component 2 was not significant, proportion of variance explained = 16.2%,  $p = 0.74$ . B) Second half, component 1 contained 57.9% of the variance,  $p < .01$ , component 2 was not significant, proportion of variance explained = 14.9%,  $p = 1.00$  C) Whole game, component 1 contained 53.6% of the variance,  $p < .01$ , component 2 was not significant, proportion of variance explained = 17.49%,  $p = 0.11$ .

Table 1: PCA component 1 and 2 factor scores, bootstrap ratios, and loadings. Values in bold represent significant results where the bootstrap ratio exceeds +/- 1.96.

<b>Component 1</b>							
	HR (bpm)	TRIMP (AU)	Total Distance (m)	Average Speed (m·min <sup>-1</sup> )	HID (m)	Accelerations (reps)	Decelerations (reps)
<b>1st Half</b>							
Factor Score (BSR)	<b>6.50 (3.70)</b>	<b>4.96 (4.89)</b>	<b>12.13 (6.78)</b>	<b>10.26 (4.80)</b>	<b>8.87 (7.62)</b>	<b>12.15 (6.66)</b>	<b>11.28 (7.60)</b>
Loading	0.48	0.37	0.90	0.76	0.66	0.90	0.84
<b>2nd Half</b>							
Factor Score (BSR)	<b>6.59 (4.16)</b>	<b>7.30 (8.15)</b>	<b>12.49 (8.88)</b>	<b>10.95 (6.17)</b>	<b>8.91 (7.91)</b>	<b>12.50 (8.29)</b>	<b>11.41 (9.12)</b>
Loading	0.49	0.54	0.93	0.81	0.66	0.93	0.85
<b>Whole Game</b>							
Factor Score (BSR)	<b>6.55 (3.80)</b>	<b>5.43 (6.71)</b>	<b>12.00 (8.33)</b>	<b>10.21 (5.17)</b>	<b>8.91 (7.69)</b>	<b>12.50 (7.14)</b>	<b>11.59 (8.02)</b>
Loading	0.49	0.40	0.89	0.76	0.66	0.91	0.86
<b>Component 2</b>							
<b>1st Half</b>							
Factor Score (BSR)	<b>7.28 (6.91)</b>	<b>-11.08 (-6.07)</b>	<b>-3.36 (-2.80)</b>	<b>2.38 (2.47)</b>	<b>3.62 (4.04)</b>	-0.93 (-0.92)	0.30 (0.29)
Loading	0.54	-0.82	0.249	0.18	0.27	-0.07	0.02
<b>2nd Half</b>							
Factor Score (BSR)	<b>8.71 (7.44)</b>	<b>-9.56 (-7.27)</b>	-1.56 (-1.35)	<b>3.96 (3.12)</b>	1.06 (1.07)	-0.14 (-0.14)	-1.70 (-1.59)
Loading	0.65	-0.71	-0.12	0.294	0.08	-0.01	-0.13
<b>Whole Game</b>							
Factor Score (BSR)	<b>9.04 (7.51)</b>	<b>-10.84 (-5.84)</b>	<b>-2.93 (-2.79)</b>	<b>3.33 (3.16)</b>	1.46 (1.55)	-0.30 (-0.28)	-0.73 (-0.82)
Loading	0.67	-0.80	-0.22	0.25	0.11	-0.02	-0.05

Abbreviations: High-intensity distance (HID), average heart rate (HR), training impulse (TRIMP), boot strap ratio (BSR)

This table also shows variables that significantly loaded onto a second principal component, but none of these second components were statistically significant. HR, TRIMP, and average speed consistently loaded onto the second component for each game segment. The first half also showed total distance and HID with significant loadings. The second half had no additional loadings. Additional loadings for the whole game included only total distance.

The means and standard deviation for each metric for the first half, second half, and whole game are shown in Table 2. Paired samples t-tests indicated differences between halves for all the metrics tested, with reduced player output in the second half. All effect sizes were considered large except for HR and TRIMP which were moderate.

**4. Discussion**

This study used PCA to assess which internal and external variables were associated with different portions of a women’s collegiate lacrosse game. To date, this is the first study to statistically evaluate game workload metrics in lacrosse or among female collegiate athletes. Analyses revealed one significant principal component for each of the three game sections analysed. These data indicate that game performance is best evaluated by both internal and external workload variables, but external workload variables tended to have higher factor loadings. This falls in line with the notion that external load variables show overall workload on the body from training or a game; whereas internal workload variables typically show response with alterations in training and fitness (Wing, 2018).

Results of the present study agree with previous literature suggesting that both external and internal workload measures should be used to understand the physiological load and variance experienced by athletes (Bunn et al., 2021; Weaving et al., 2014; Weaving et al., 2017). Bunn et al. (2021) previously evaluated these same metrics in relation to different training modes in lacrosse with the same population. The results of the present study are compared to this previous work in Table 3. Four training modes—individual skills, stick work, team drills, and conditioning—included two principal components with external workload variables significantly loading onto the first component and internal variables loading onto the second. Small-sided games

was the only training mode that included only one principal component with only external variables. Total distance, accelerations, and decelerations strongly loaded onto the first component extracted for all five training modes and all three game sections. HID loaded onto the first component for all three game sections, but only for the conditioning training mode. Average speed registered onto the first component for individual skills, stick work, small-sided games, team drills and onto the second component for conditioning. However, it only registered for the second half of games onto the first component. This is interesting because all game speed means were higher than most drill speed means (excluding conditioning). This may suggest the added importance of speed late in the game. According to the descriptive data in Table 1, the average speed is slightly lower in the second half, but the variance is higher. This may indicate that the speed of players in the games are typically near their maximum in the first half. There is greater variability in speed in the second half because players are more selective about when to use maximum speed which is supported by fewer accelerations in the second half as well. Lastly, TRIMP loaded onto the first component for all three game sections, but never for the five training modes. This may be due to the difference in n-size between the two studies. The present study selected only the key players from games, whereas the training study included a larger portion of the team. Further, the 12 players evaluated in games represented three different positions (attacker, midfielder, and defender, n = 4 for each position) playing different roles during the game, where they would all have been working in the same drill modes with the training study.

From a practitioner perspective it would be ideal if metrics from training aligned with the metrics from each game section. Because HID loaded onto the first component for all three game sections, but only one of the five training modes, alterations in training should be considered to incorporate more HID into training. Average speed was the only metric measured relative to time, and it loaded onto the first component for four training modes and all three game sections. Comparatively, the average speed is higher in games (50.5-53.2 m·min<sup>-1</sup>) than the four training modes in which it loaded (35-44 m·min<sup>-1</sup>). A practical consideration would be to increase average speed during training such as team drills and stick work to match that of game speed.

Table 2: Means and standard deviations of each metric for the first half, second half, and total game. Differences between the two halves (*p* < .05) are shown with \* and effect sizes (ES) are shown with the paired t-test *p*-values.

	Distance (m)	Average speed (m·min <sup>-1</sup> )	HID (m)	HR (bpm)	Accelerations (count)	Decelerations (count)	TRIMP (AU)
First Half	3061.9 ± 645.7	53.2 ± 11.2	262.5 ± 118.9	161.1 ± 16.2	89.3 ± 27.7	15.6 ± 5.9	215.2 ± 18.7
Second Half	2651.7 ± 548.5	50.5 ± 10.5	191.5 ± 83.3	155.5 ± 16.0	69.1 ± 22.4	11.7 ± 4.2	204.5 ± 17.3
Total	6205.0 ± 1767.2	50.7 ± 11.5	454.7 ± 265.9	158.4 ± 42.6	160.1 ± 64.4	27.5 ± 14.0	465.0 ± 130.6
<i>p</i> -value (ES)	< .01 (2.13)*	.01 (0.82)*	< .01 (1.47)*	.04 (0.57)*	< .01 (2.31)*	< .01 (1.51)*	.02 (0.69)*

Abbreviations: High-intensity distance (HID), average heart rate (HR), training impulse (TRIMP), arbitrary units (AU)

Table 3: Comparisons between PCA loadings between games (shaded in gray) and training (Bunn et al., 2021).

	Whole Game	1 <sup>st</sup> Half	2 <sup>nd</sup> Half	Individual Skills	Stick Work	Small-sided Games	Team Drills	Conditioning
<b>1<sup>st</sup> Component</b>								
Total Distance	✓	✓	✓	✓	✓	✓	✓	✓
HID	✓	✓	✓					✓
Accelerations	✓	✓	✓	✓	✓	✓	✓	✓
Decelerations	✓	✓	✓	✓	✓	✓	✓	✓
Average Speed	✓	✓	✓	✓	✓	✓	✓	
TRIMP	✓	✓	✓					
HR	✓	✓	✓					
<b>2<sup>nd</sup> Component</b>								
HID							✓	
Average Speed							✓	✓
TRIMP				✓	✓		✓	✓
HR					✓			

Abbreviations: High-intensity distance (HID), average heart rate (HR), training impulse (TRIMP)

Previous work in sports science suggests prioritizing training metrics that contribute to alterations in performance and fitness (Akubat et al., 2012; Manzi et al., 2009). If making selections in metrics based from game factor loadings, prioritizing total distance, HID, accelerations, decelerations, and TRIMP would be sensible. Creating focal points with aims to meet certain threshold values for each external metric during training would likely then result in positive changes in fitness and therefore TRIMP. As fitness improves, TRIMP would decrease, and it would respond appropriately to other stimuli such as physiological stress and recovery.

In addition to providing analyses to evaluate important variables within women’s lacrosse, these data also add to the small body of literature available for match profiles within this sport (Devine et al., 2020; Hauer et al., 2019). Devine et al. (2020) provided data for collegiate female lacrosse game profiles and Hauer et al. (2019) provided similar data for elite international competition in women’s lacrosse. The microtechnology equipment (VX Sport) and population of study were the same between Devine et al. (2020) and the present study. Comparing game profiles, the present study indicated higher total distance and accelerations than Devine et al. (2020), but lower HID. Compared to Hauer et al. (2019), the present study showed greater total distance, accelerations (zone 4), and decelerations (zone 4). Accelerations, decelerations, and total distance were all defined similarly between the three studies and indicated variation with these metrics. Further research should be conducted to assess if this is due to talent or skill differences or is more related to different styles of play

One limitation of this study was that playing time of the athletes during games or by half was not monitored. In the game of lacrosse, substitutions occur freely, so tracking playing time without the use of video assistance was problematic. This could have affected the differences noted in metrics between the first and second halves if the substitution strategy was different between the two halves. The small n-size utilized in this study

may also be a limitation for PCA of games due to the different roles of the three lacrosse positions.

Training and game workloads in collegiate women’s lacrosse are not yet well-understood. These data highlighted the importance of the internal and external metrics in women’s collegiate lacrosse games, and that factor loading patterns were different between games and different training modes. The results of this study suggest metrics related to external workload with the addition of TRIMP may be most useful in representing load during competition. The variation in first to second half workload suggest an imbalance most simply attributed to conditioning. A more thorough understanding of workload during competition may assist sports scientists in planning training programs better suited to meet the demands experienced during competition. Lastly, it is difficult to predict if the results of the present PCA analyses would be identical for other women’s collegiate lacrosse teams, but this is at minimum a starting point for narrowing important metrics and providing ideas for analyses. Further research should be conducted to compare load metrics over multiple seasons and across multiple teams to determine the validity of the current findings.

**Conflict of Interest**

The authors have no conflicts of interest to declare.

**Acknowledgment**

We would like to thank the Campbell University lacrosse team and coaches for their participation with this research project.

**References**

Abdi, H., & Williams, L. J. (2010). Principal component analysis. *Wiley Interdisciplinary Reviews: Computational Statistics*, 2(4), 433–459. <https://doi.org/10.1002/WICS.101>

- Akenhead, R., & Nassis, G. P. (2016). Training load and player monitoring in high-level football: Current practice and perceptions. *International Journal of Sports Physiology and Performance*, 11(5), 587–593. <https://doi.org/10.1123/ijpspp.2015-0331>
- Akiyama, K., Sasaki, T., & Mashiko, M. (2019). Elite male lacrosse players' match activity profile. *Journal of Sports Science and Medicine*, 18(2), 290–294.
- Akubat, I., Patel, E., Barrett, S., & Abt, G. (2012). Methods of monitoring the training and match load and their relationship to changes in fitness in professional youth soccer players. *Journal of Sports Sciences*, 30(14), 1473–1480. <https://doi.org/10.1080/02640414.2012.712711>
- Alphin, K. H., Hudgins, B. L., & Bunn, J. A. (2019). Intensity classification of drills for a collegiate women's lacrosse team: An observational study. *International Journal of Kinesiology and Sports Science*, 7(3), 16–21. <https://doi.org/10.7575/aiac.ijkss.v.7n.3p.16>
- Alphin, K. L., Sisson, O. M., Hudgins, B. L., Noonan, C. D., & Bunn, J. A. (2020). Accuracy assessment of a GPS device for maximum sprint speed. *International Journal of Exercise Science*, 13(4), 273–280.
- Beaton, D., Abdi, H., & Filbey, F. (2014). Unique aspects of impulsive traits in substance use and overeating: Specific contributions of common assessments of impulsivity. *The American Journal of Drug and Alcohol Abuse*, 40(6), 463–475. <https://doi.org/10.3109/00952990.2014.937490>
- Bunn, J. A., Myers, B. J., & Reagor, M. (2021). An evaluation of training load measures for drills in women's collegiate lacrosse. *International Journal of Sports Physiology and Performance*, 16(6), 841–848. <https://doi.org/https://doi.org/10.1123/ijpspp.2020-0029>
- Cohen, J. (1988). *Statistical Power Analysis for the Behavioural Science* (2nd ed.). Hillsdale, NJ: Erlbaum.
- Devine, N. F., Hegedus, E. J., Nguyen, A.D., Ford, K. R., & Taylor, J. B. (2020). External match load in women's collegiate lacrosse. *Journal of Strength and Conditioning Research*, Advance online publication. <https://doi.org/10.1519/jsc.0000000000003451>
- Hauer, R., Tessitore, A., Hauer, K., & Tschan, H. (2019). Activity profile of international female lacrosse players. *Journal of Strength and Conditioning Research*, Advance online publication. <https://doi.org/10.1519/jsc.0000000000003253>
- Malone, S., Doran, D., Collins, K., Morton, J., & McRobert, A. (2014). Accuracy and reliability of VXsport global positioning system in intermittent activity. *Proceedings of the 19<sup>th</sup> Annual Congress of the European College of Sports Science*, 409.
- Manzi, V., Iellamo, F., Impellizzeri, F., D'Ottavio, S., & Castagna, C. (2009). Relation between individualized training impulses and performance in distance runners. *Medicine and Science in Sports and Exercise*, 41(11), 2090–2096. <https://doi.org/10.1249/MSS.0b013e3181a6a959>
- McLaren, S. J., Macpherson, T. W., Coutts, A. J., Hurst, C., Spears, I. R., & Weston, M. (2018). The relationships between internal and external measures of training load and intensity in team sports: A meta-analysis. *Sports Medicine*, 48(3), 641–658. <https://doi.org/10.1007/s40279-017-0830-z>
- National Collegiate Athletic Association. (2019). ® *Sports Sponsorship and Participation Rates*. <https://www.ncaa.org/>
- Polley, C. S., Cormack, S. J., Gabbett, T. J., & Polglaze, T. (2015). Activity profile of high-level Australian lacrosse players. *Journal of Strength and Conditioning Research*, 29(1), 126–136. <https://doi.org/10.1519/JSC.0000000000000599>
- R Core Team (2013). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing, Vienna, Austria. <http://www.r-project.org/>
- The jamovi project (Version 1.2). (2020). <http://www.jamovi.org>
- Vanrenterghem, J., Nedergaard, N. J., Robinson, M. A., & Drust, B. (2017). Training load monitoring in team sports: A novel framework separating physiological and biomechanical load-adaptation pathways. *Sports Medicine*, 47(11), 2135–2142. <https://doi.org/10.1007/s40279-017-0714-2>
- Weaving, D., Beggs, C., Dalton-Barron, N., Jones, B., & Abt, G. (2019). Visualizing the complexity of the athlete-monitoring cycle through principal-component analysis. *International Journal of Sports Physiology and Performance*, 14(9), 1304–1310. <https://doi.org/10.1123/ijpspp.2019-0045>
- Weaving, D., Marshall, P., Earle, K., Nevill, A., & Abt, G. (2014). Combining internal- and external-training-load measures in professional rugby league. *International Journal of Sports Physiology and Performance*, 9(6), 905–912. <https://doi.org/10.1123/ijpspp.2013-0444>
- Weaving, D., Jones, B., Marshall, P., Till, K., & Abt, G. (2017). Multiple measures are needed to quantify training loads in professional rugby league. *International Journal of Sports Medicine*, 38(10), 735–740. <https://doi.org/10.1055/s-0043-114007>
- Wing, C. (2018). Monitoring athlete load: Data collection methods and practical recommendations. *Strength and Conditioning Journal*, 40(4), 26–39. <https://doi.org/10.1519/SSC.0000000000000384>