INTERNATIONAL JOURNAL OF
-EXERCISE SCIENCE-

*Original Research*

# GPS External Load Metric Data and Game Performance in NCAA Division I Women's Lacrosse Athletes: A Longitudinal Study

Rachel M. Lifson*[1], Xavier Smith‡[2,3], Ernest Rimer‡[2,3], Andreas Stamatis‡[1,2]

[1]Health and Sport Sciences, University of Louisville, Louisville, KY, United States; [2]Institute of Sports Medicine, University of Louisville Health, Louisville, KY, United States; [3]Athletic Department, University of Louisville, Louisville, KY, United States

*Denotes student, ‡Denotes established investigator

## Abstract

***International Journal of Exercise Science 18(8): 130-146, 2025.*** https://doi.org/10.70252/CUVE9138 This study investigates the relationship between GPS-derived external load metrics and game performance (win/loss) in NCAA Division I women's lacrosse athletes. Utilizing data from three seasons (2022-2024), the study analyzed 1,687 observations from 54 players to identify key performance indicators correlating with game outcomes. GPS metrics including Total Distance (TD), High-Speed Distance (HSD), Very High-Speed Efforts (VHSE), Total Player Load (TPL), High Inertial Movement Analysis (High IMAs), and Total Acceleration Load (TAL) were assessed. Multivariate logistic regression results indicate that VHSE is the most significant predictor of game success, with VHSE showing a positive correlation with winning outcomes ($p$ = 0.007; OR = 1.017, 95% CI [1.005, 1.030]). Although other metrics like TD and TPL were significant in univariate models, their impact diminished in multivariate analysis, suggesting their effects are intertwined with other performance factors. The study highlights the importance of high-intensity efforts in game outcomes and provides insights for optimizing training strategies for female lacrosse athletes. These findings underscore the need for continued research into female athlete performance to better inform sport-specific training programs and enhance competitive success.

Keywords: Athlete profiling, performance analysis, training optimization, physiological stressors, Catapult

## Introduction

The sport of lacrosse, affiliated with the National Collegiate Athletics Association (NCAA) — a nonprofit organization encompassing three divisions of athletics whose mission is to provide a world-class athletic and academic experience for student-athletes in the United States — is one of the oldest organized sports in history, dating back to its inception in the 12th century.[1] Women's lacrosse was not established until the late 1800s and did not arrive in the United States until 1931, centuries after the game itself was invented.[2] Despite its late beginning in the United States, women's lacrosse has become one of the fastest growing and physically demanding sports to exist in the world today. Across all three divisions of the NCAA, there are currently more than five hundred collegiate women's lacrosse programs, over one hundred more than the number of men's collegiate programs in the United States.[3] Recognized as the "fastest game on two feet," the sport of women's lacrosse requires incredible demands from its athletes in terms of aerobic fitness, speed, and agility.[4]

Regardless of the praise and popularity women's lacrosse has received in recent years, it is undeniable that female sports have been severely underrepresented in research throughout history, an issue that still exists today.[6] The literature reveals significant gaps in understanding the physiology and sport performance of female athletes compared to their male counterparts.[7] There are significant physiological differences between men and women, all of which can impact sport performance and responses to exercise; a primary reason for the need for more female-specific sport science research to correlate with the increases in participation of the sport.[7]

The implementation of *Global Positioning System* (GPS) data over the past decade has become crucial for monitoring athlete performance and providing insight on specific physiological demands for sports.[5,8] GPS technology provides comprehensive data into monitoring external load metrics (e.g., distance, speed), with goals of maximizing performance for athletes.[9] GPS data is becoming more prevalent and relied upon in all sports; however, to date, there is not enough data or research available for the sport of women's lacrosse that can attest to describing performance levels at any level of experience (athlete profiling).[5,10,11]

There has been ample research to suggest that wearable GPS technology is a valid and reliable way of analyzing sport-specific movements and developing athlete profiles.[8,10] It is important to recognize that while many sports may possess similar characteristics, demands of specific sports can be quite different, which is why athlete profiling is vital for analyzing women's lacrosse athletes, especially as the norms for training volume are still unclear.[12] One of the primary goals of implementing GPS external load metric data monitoring into elite sports is to understand their specific demands and the physiological stressors placed on these athletes.[9] It has been found that women's lacrosse requires extensive levels of external load, specifically high intensity efforts; a finding that is imperative to address when programming for these athletes to ensure they are prepared for competition.[13]

There are numerous *Key Performance Indicators* (KPIs) that GPS technology can attain for the sport of women's lacrosse in attempts to correlate to game performance (win/loss) and understand requirements of the athletes.[9] Despite the limited research, KPIs that have been used and suggested as the potential basis to assess the stressors placed on female lacrosse athletes thus far include *Total Distance* (TD; the total amount of distance in meters in which athletes cover in a training session), *Total Player Load* (1) (TPL; the sum of accelerations across all axes of a tri-axial accelerometer), *High-Speed Distance* (HSD; the amount of meters covered above 11.2 mph), *Total Acceleration Load* (TAL; the accumulation of absolute acceleration values derived from smoothed velocity and sampled at 10Hz), and *Very High-Speed Efforts* (VHSE; any effort that produces a speed that is ≥ 75% of an athlete's maximum velocity), along with more sport specific indicators, such as *High Inertial Movement Analysis* [High IMAs; a measure of fast (above 3.5 m*s-1) Accelerations + Decelerations + High Change of Direction Left + High Change of Direction

Right].[13–17] Previous literature has suggested that game performance is best evaluated by using internal and external load metrics, although external workload variables prove to have higher factor loadings; following the trend that external load metrics indicate stress on the body from games and/or training; a primary reason for the focus on external load key performance indicators in the present study.[18]

It has been found in previous studies analyzing the peak average acceleration during women's lacrosse competition that similar to other sports, there tends to be a noticeable decrease in average acceleration as moving duration increases.[5] Since the addition of a 90-second shot clock, resulting in a new emphasis on transition in women's lacrosse competition, it has been found that tracking acceleration and deceleration for these players is imperative in this sport.[5] Tracking accelerations and decelerations has been important especially when focusing on positional differences, as in Calder et al.'s study, they found that due to the new rules of the game, defender acceleration outputs tend to be greater when compared to attackers; and that midfielders tend to have the highest intensity running outputs out of all positions.[5]

It is also important to include the fact that since the rule change in 2021 where NCAA women's lacrosse would be playing four 15-minute quarters rather than two 30-minute halves, that this new game format has proved to present a greater demand on players, emphasizing the need for high-intensity efforts and a greater anaerobic demand.[19] This information can be significant for coaches and sport scientists for developing training plans to highlight the need for these new demands.[19]

The inferences that can be made from analyzing KPIs, such as TD, TPL, HSD, TAL, VHSE, and High IMAs, may prove fundamental for aiding sport scientists and coaches in improving their women's lacrosse training techniques to ultimately enhance their athletes' physical capabilities. To assist furthering the current literature, the purpose of this study is to explore the relationship between Total Distance, Total Player Load, High- Speed Distance, Total Acceleration Load, Very High-Speed Efforts, and High IMAs and game outcomes (wins, losses) across three NCAA Division I ACC women's lacrosse seasons.

## Methods

### *Participants*

The sample for this study comprised female Division I lacrosse players from an Atlantic Coast Conference (ACC) institution. The (cleaned) dataset includes a total of 1,687 observations collected over three seasons (2022, 2023, and 2024). Each observation corresponds to a player's performance metrics (i.e., Total Distance, High-Speed Distance, Very High-Speed Efforts, Total Player Load, High IMAs, Total Acceleration Load) recorded during individual games, providing a robust dataset for analyzing the relationship between GPS-derived performance metrics and game outcomes. The number of unique players in the sample was 54, with 21 players having data from 1 year, 17 players from 2 years, and 15 players from 3 years. The dataset used for this study was provided in a cleaned format and did not include specific information on players' roles, such as whether they were starters, key players, or bench players. As a result, we were unable to differentiate between these groups in our analysis.

*Protocol*

This study was conducted under the auspices of the approved omnibus Institutional Review Board (IRB) protocol (#21.0866). Initially, the primary objective of data collection was intended for clinical and practical applications. Subsequently, this retrospective data was repurposed for research, aligning with the stipulations of the existing omnibus IRB. Throughout the study, strict adherence to the IRB's ethical guidelines was maintained, ensuring the protection and confidentiality of all participant information. This research was conducted in full compliance with the ethical standards established by the *International Journal of Exercise Science*.[20] This study was a hypothesis-generating study based on a convenience sample; therefore, power analysis was not necessary.[21]

In more detail, the performance data were collected using the Catapult Vector S7 (Catapult, Melbourne, Australia) device, a professional-grade GNSS system designed for elite athlete performance measurement. The Vector S7 device is equipped with various sensors, including a GNSS module (10Hz GNSS / 18Hz GPS), tri-axial accelerometer (up to 1000 Hz), tri-axial gyroscope (up to 1000 Hz), tri-axial magnetometer (up to 1000 Hz), magnetic heart rate receiver, ECG heart rate board (up to 250Hz), Bluetooth Low Energy, and an ultra-wide band (UWB) antenna.

Data collection involved several steps to ensure accurate and reliable performance metrics. First, each Vector S7 device was charged using the Vector Dock and configured via USB serial connection to the OpenField software, with athletes assigned to devices using the 'auto-assign' feature. Live sessions were initiated by connecting Vector Anchors via USB and starting live data transmission once GNSS lock was obtained. Recording periods were managed through the console interface, and live data was monitored for accuracy. After sessions, devices were turned off, placed back in the Vector Dock, and data was transferred to the PC for further analysis. Data synchronization with the OpenField cloud ensured secure storage and accessibility.

*Statistical Analysis*

The statistical analysis was conducted using MATLAB (2024a), following a systematic approach to ensure thorough examination and replicability of the study. Initially, the dataset was cleaned to handle any missing values and identify outliers. Descriptive statistics were calculated for each variable, and visualizations such as histograms and box plots were created to understand data distribution. Pearson correlation coefficients were then calculated to assess linear relationships between each GPS metric and game outcome. Effect sizes for Pearson correlations were interpreted based on the correlation coefficient ($r$), with values of 0.10, 0.30, and 0.50 representing small, medium, and large effects, respectively. Logistic regression models were fitted to explore the relationship between GPS metrics and game outcome, with univariate models assessing each predictor individually and a multivariate model considering all predictors simultaneously. Odds ratios (OR) were reported as the effect size for logistic regression models, along with 95% confidence intervals (CI) to provide a measure of precision for these estimates. An alpha level of 0.05 was set to determine statistical significance for all analyses. ROC curves assessed the accuracy of the logistic regression models by displaying the trade-off between sensitivity (true positive rate) and specificity (false positive rate). This comprehensive analysis identified key performance metrics related to game outcomes. For replication purposes, we provide MATLAB scripts of the code used for those analyses in Appendix A.

## Results

### *Data Cleaning and Preparation*

The initial dataset consisted of 1,687 observations of female Division I lacrosse players from an ACC institution over three seasons (2022-2024). The number of wins and losses per year are shown in Table 1. This table provides an overview of the team's performance in terms of game outcomes (wins/losses) for each of these three seasons. It sets the context for understanding how the GPS metrics relate to the team's success and highlights fluctuations in team performance that may correlate with changes in GPS-derived performance metrics across seasons. On average, each player participated in $M$ = 31.83 games ($SD$ = 16.03) over the three seasons, reflecting variability in individual game participation across the dataset. Please, note that two games from the 2024 season are not included due to technical issues in that specific field (away games against the same team). The data cleaning process included handling missing values and identifying outliers. No missing values were found in any of the columns, indicating high data quality. Outliers were identified using z-scores. The number of outliers for each variable is summarized in Table 2. This table summarizes the outliers detected for each GPS metric. By identifying outliers, we ensured that the data used for analysis was robust and free from extreme values that could skew results. This step was critical for maintaining data integrity and producing valid results.

**Table 1.** Wins and losses per season

| Season | Wins | Losses |
|---|---|---|
| 2022 | 7 | 11 |
| 2023 | 5 | 12 |
| 2024 | 8 | 11 |

**Table 2.** Number of outliers for each GPS metric

| Variables | Number of Outliers |
|---|---|
| Total Distance[a] | 0 |
| High Speed Distance[b] | 20 |
| Very High-Speed Efforts[c] | 25 |
| Total Player Load[d] | 0 |
| High IMAs[e] | 7 |
| Total Acceleration Load[f] | 0 |

[a]Total Distance (TD): Measured in meters (m) or kilometers (km), representing the total distance an athlete covers during a session. [b]High-Speed Distance (HSD): Expressed in meters (m), indicating the distance covered while running at speeds above a predefined threshold, often set at 5 meters per second. [c]Very High-Speed Efforts (VHSE): Counted as a simple tally, representing the number of efforts where the athlete's speed exceeds a higher threshold,

such as 7 meters per second. [d]Total Player Load (TPL): A unitless metric calculated from accelerometer data, reflecting the cumulative load experienced by the athlete. [e]High Inertial Movement Analysis (High IMAs): Counted as a simple tally, indicating the number of high-intensity movements detected by accelerometers and gyroscopes, such as accelerations, decelerations, and changes of direction. [f]Total Acceleration Load (TAL): A unitless metric derived from the sum of all accelerations, providing insight into the overall acceleration demands placed on the athlete.

*Descriptive Statistics*

Summary statistics for each variable after removing outliers are presented in Table 3. This table presents the mean, standard deviation, minimum, and maximum values for each performance metric, allowing to understand the distribution and variability of the data across players and games. The descriptive statistics served as a foundation for understanding how each GPS metric might contribute to game outcomes, providing a baseline before further analysis was conducted.

**Table 3.** Descriptive statistics for performance metrics and game outcomes (cleaned data)

| Variable | Mean/SD | Min | Max |
|---|---|---|---|
| Total Distance (meters) | 5479.5/2833.77 | 2783.90 | 12814 |
| High Speed Distance (meters) | 1107.3/915.75 | 857.5 | 3894.4 |
| Very High-Speed Efforts (number of efforts) | 16.3/18.81 | 17.90 | 95 |
| Total Player Load (unitless metric) | 585.4/304.66 | 299.4 | 1460.3 |
| High IMAs (number of high-intensity movements) | 18.4/19.56 | 19.40 | 380 |
| Total Acceleration Load (unitless metric) | 1716.6/886.85 | 874.20 | 3919.6 |

Figures 1-6 show box plots for each GPS metric, highlighting the distribution of data for both wins and losses. The six box plots presented in this section display the distribution of various GPS-derived performance metrics in relation to game outcomes (coded as 0 = Loss, 1 = Win). Each box plot offers a visual representation of how these metrics vary across games that were won and lost, helping to identify which variables might have the most influence on performance success in this women's lacrosse team. In general, the median values across metrics are generally comparable between wins and losses, with subtle differences in some cases (e.g., Very High-Speed Efforts), and while the interquartile range (IQR) is similar for most metrics, some (e.g., Total Acceleration Load, Very High-Speed Efforts) display more variability in one outcome category; the whiskers indicate a similar overall range for both outcomes, though losses tend to have slightly more variability, with outliers present in most metrics and particularly extreme values in losses for High-Speed Distance and Very High-Speed Efforts. Histograms and boxplots (Figures 8-19) for each GPS metric for all games are included in the Appendix B.

*Correlation Analysis*

Pearson correlation coefficients between each GPS metric and game outcome are shown in Table 4. This table shows the correlation coefficients between each GPS metric and the binary game outcome (win/loss). The correlations ranged from 0.0152 to 0.0781, indicating weak linear relationships. Although the correlations are weak, they help identify preliminary relationships between the GPS-derived metrics and game success. This table highlights which variables are potentially more meaningful in predicting game outcomes.

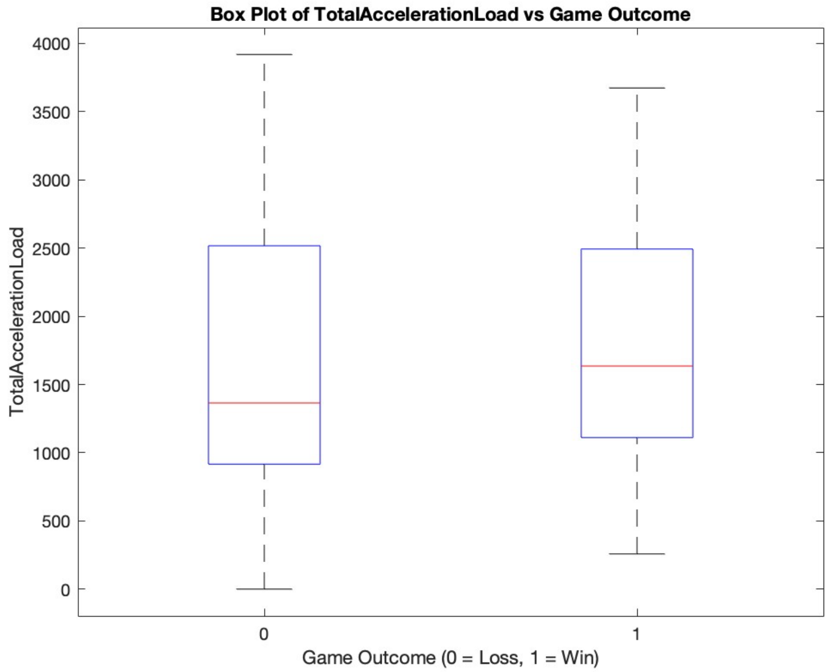


**Figure 1.** Box plot of total acceleration load (unitless metric) vs game outcome

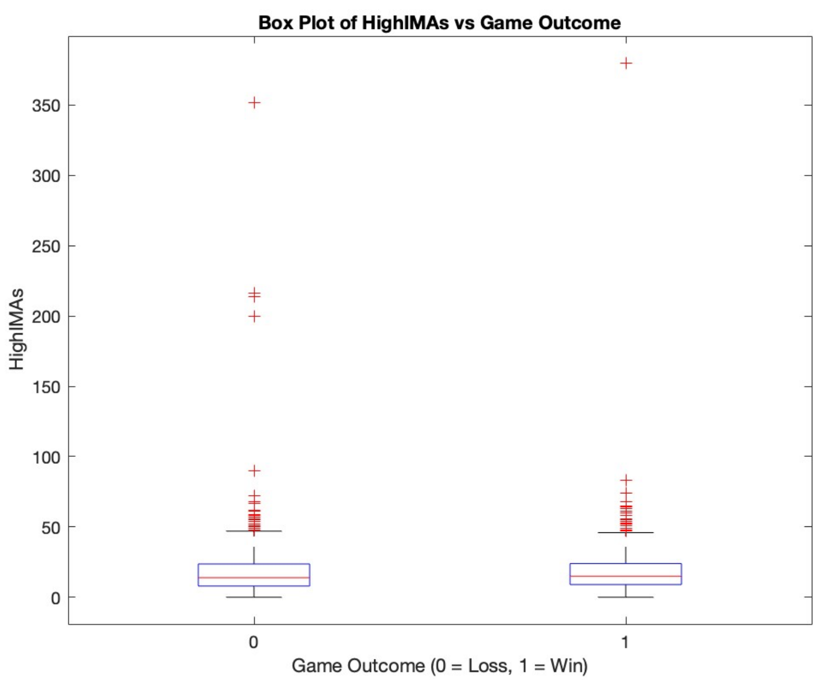


**Figure 2.** Box plot of high IMA's (number of high-intensity movements) vs game outcome

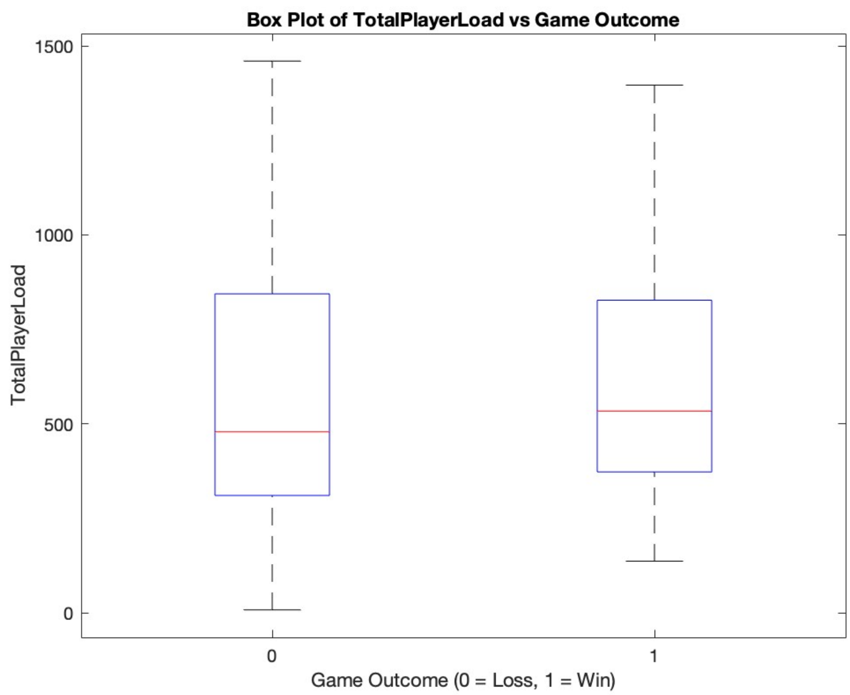


**Figure 3.** Box plot of total player load (unitless metric) vs game outcome

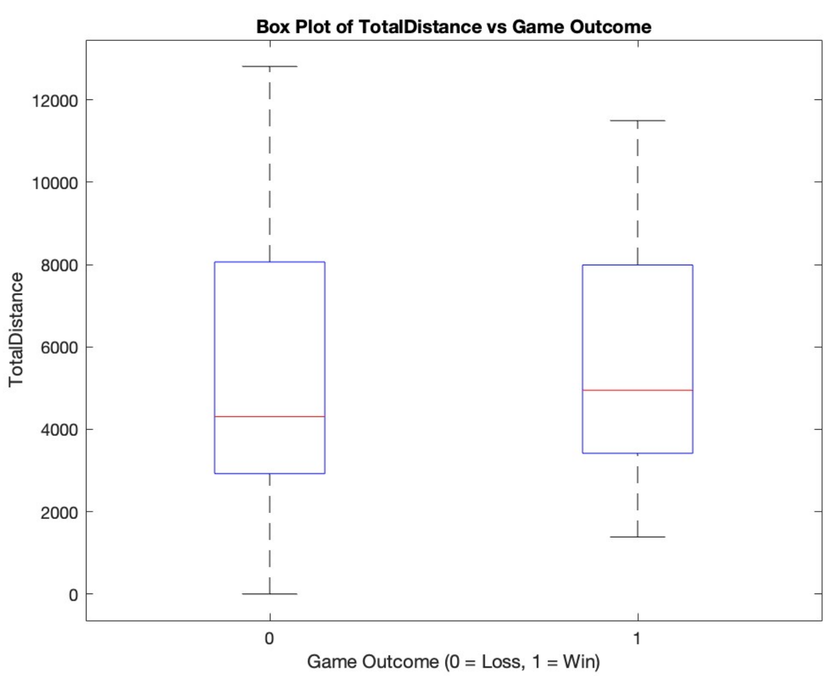


**Figure 4.** Box plot of total distance measured in meters (m) vs game outcome

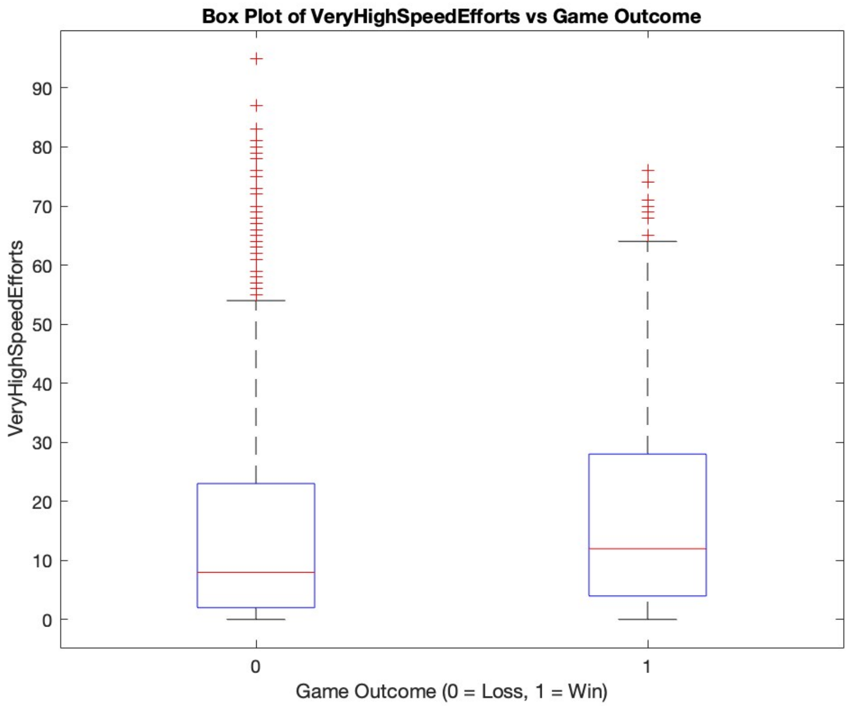


**Figure 5.** Box plot of very high-speed efforts (number of efforts) vs game outcome

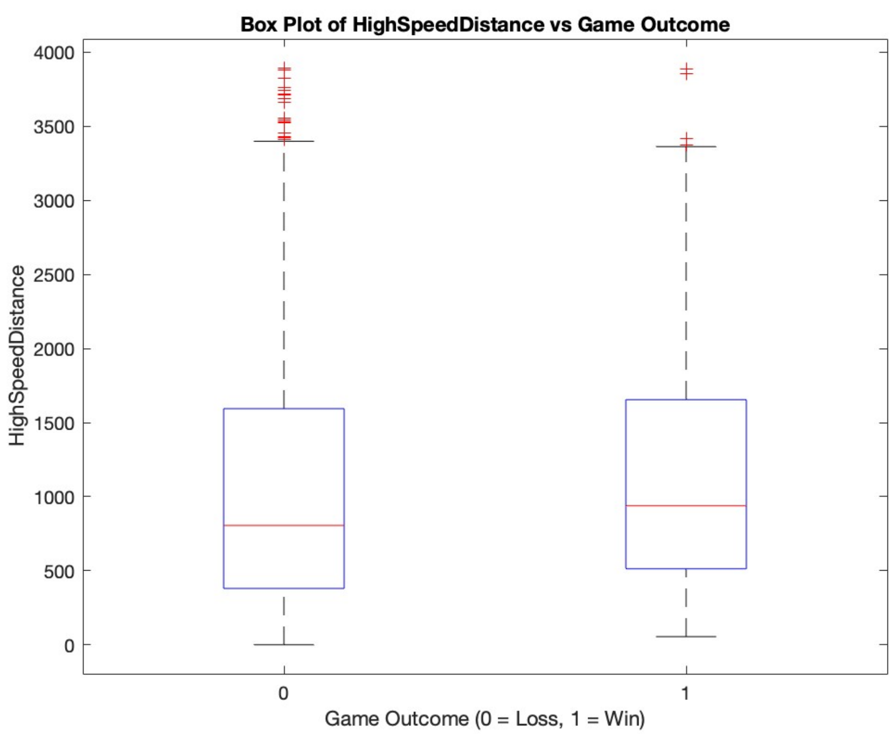


**Figure 6.** Box plot of high-speed distance expressed in meters (m) vs game outcome

**Table 4.** Pearson Correlation Coefficients Between GPS Metrics and Game Outcome

| Variable | Correlation with Match Code (2) |
|---|---|
| Total Distance | 0.0505 |
| High Speed Distance | 0.0407 |
| Very High-Speed Efforts | 0.0781 |
| Total Player Load | 0.0495 |
| High IMAs | 0.0152 |
| Total Acceleration Load | 0.0659 |

*Logistic Regression Analysis*

1. Multivariate Logistic Regression

A multivariate logistic regression was performed to examine the relationship between the GPS metrics and game outcome. The results are presented in Table 5.

**Table 5.** Multivariate logistic regression results

| Variable | Estimate | SE | tStat | pValue |
|---|---|---|---|---|
| Intercept | -0.69881 | 0.1206 | -5.7946 | 6.8503e-09 |
| Total Distance | -0.0002071 | 0.0001362 | -1.5201 | 0.1285 |
| High Speed Distance | -0.0002425 | 0.0001517 | -1.5988 | 0.1099 |
| Very High-Speed Efforts | 0.01693 | 0.006261 | 2.7043 | 0.0068* |
| Total Player Load | 0.0006922 | 0.0008559 | 0.8087 | 0.4187 |
| High IMAs | -0.001453 | 0.003092 | -0.4699 | 0.6384 |
| Total Acceleration Load | 0.000521 | 0.0002882 | 1.8076 | 0.0707 |

*p<.05

In the multivariate logistic regression analysis, VHSE were significantly associated with game outcomes, OR = 1.017, 95% CI [1.005, 1.030], $p$ = .007. In more detail, in this combined model, VHSE is the only metric that demonstrates a statistically significant positive association with game outcomes. The other metrics do not independently contribute to game success in this context, as their p-values are above 0.05 and their confidence intervals include 1.

The ROC curve in Figure 7 demonstrates the model's ability to classify outcomes by plotting the true positive rate (sensitivity) against the false positive rate (1-specificity) at various thresholds. With an AUC of 0.5736, the model shows moderate discriminatory power, performing better than random guessing (AUC = 0.5).

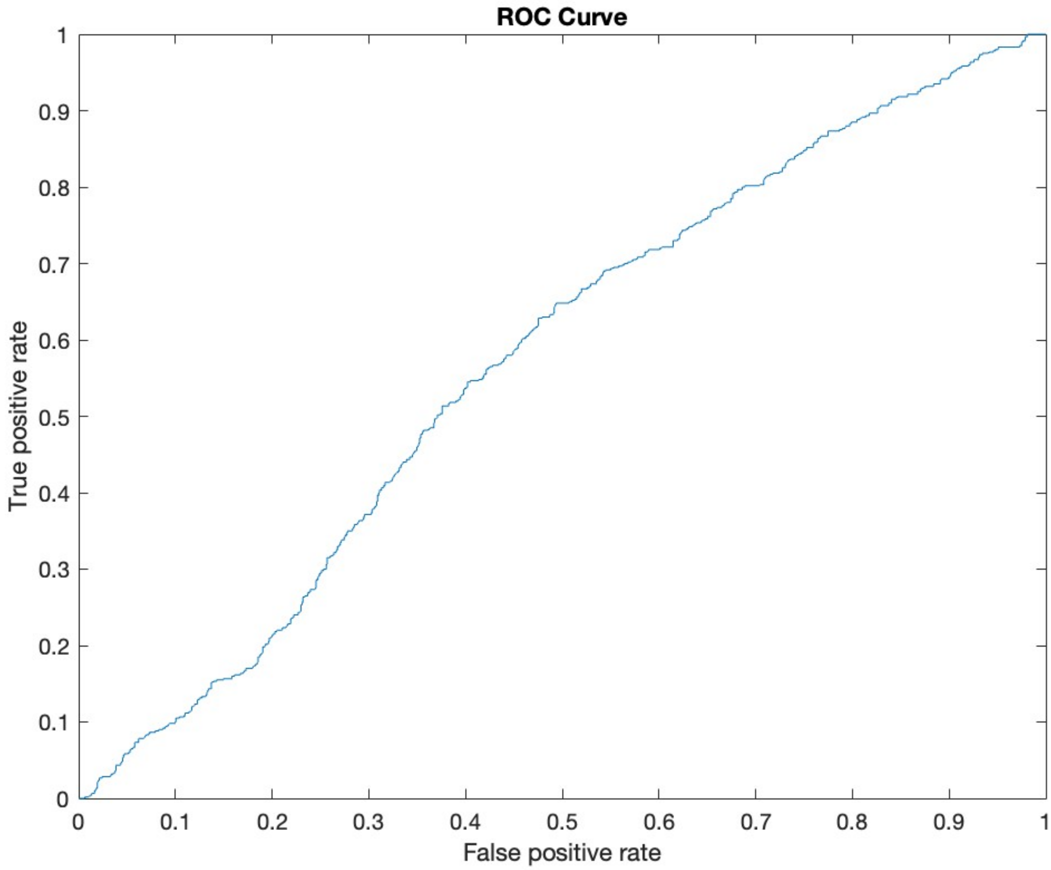


**Figure 7.** ROC curve for multivariate logistic regression model

2. Univariate Logistic Regression

Univariate logistic regression models were also performed for each GPS metric individually. The results are summarized in Table 6.

**Table 6.** Univariate Logistic Regression Results

| Variable | Estimate | SE | tStat | pValue | AUC |
|---|---|---|---|---|---|
| Total Distance | 3.7498e-05 | 1.8366e-05 | 2.0416 | 0.0412 | 0.5496 |
| High Speed Distance | 9.7651e-05 | 5.937e-05 | 1.6448 | 0.1000 | 0.5417 |
| Very High-Speed Efforts | 0.008868 | 0.002819 | 3.1456 | 0.0017 | 0.5805 |
| Total Player Load | 0.0003415 | 0.0001707 | 2.0013 | 0.0454 | 0.5459 |
| High IMAs | 0.001584 | 0.002584 | 0.6129 | 0.5400 | 0.5183 |
| Total Acceleration Load | 0.0001558 | 5.853e-05 | 2.6624 | 0.0078 | 0.5585 |

In the univariate logistic regression analysis, several variables demonstrated significant associations with game outcomes. Very High-Speed Efforts (VHSE) showed a notably significant relationship, with an odds ratio (OR) of 1.009, 95% CI [1.003, 1.014], and a p-value of

.002, indicating a meaningful predictive value for game success (i.e., For each additional high-speed effort, the odds of winning increase by 0.9%). Total Acceleration Load (TAL) also emerged as a significant predictor, albeit with a minimal effect size, having an OR of 1.00016, 95% CI [1.00004, 1.00027], and a p-value of .008 (i.e., Each additional unit of acceleration load increases the odds of winning by 0.016%). Similarly, Total Distance (TD) was associated with game outcomes with an OR of 1.00004, 95% CI [1.000002, 1.00008], and a p-value of .041 (i.e., For each additional meter covered, the odds of winning increase by 0.004%). Lastly, Total Player Load was marginally significant with an OR of 1.00034, 95% CI [1.00001, 1.00068], and a p-value of .045 (i.e., Each additional unit of player load corresponds to a 0.034% increase in the odds of winning

ROC curves (Figures 20-25) for each univariate model are provided in Appendix C.

## Discussion

The primary aim of this study was to examine the relationship between various GPS-derived performance metrics and game outcomes (wins, losses) in NCAA Division I ACC women's lacrosse over three seasons (2022-2024). This research fills a critical gap in understanding the physiology and performance of female lacrosse athletes, and their response to exercise interventions, a field that has been historically underrepresented.[7,22] The analysis revealed that among the numerous metrics studied, Very High-Speed Efforts (VHSE) was the most significant predictor of game outcomes.

As far as the key findings and potential mechanisms are concerned, the multivariate logistic regression model highlighted VHSE as a significant predictor of game success, with higher values of VHSE associated with a greater likelihood of winning in women's lacrosse ($p = 0.007$); OR = 1.017, 95% CI [1.005, 1.030]. This means that an increase in VHSE is linked to a 1.7% higher chance of achieving favorable game outcomes, indicating that more intense efforts during games can slightly improve performance, a factor that coaches and athletes may consider for training and game strategy enhancements. Finding that higher VHSE values are associated with higher winning percentage suggests that the frequency of high-speed efforts is crucial for competitive performance in women's lacrosse, likely due to the sport's dynamic and high-intensity nature.[10,12,13,23,24] VHSE may reflect players' ability to perform rapid sprints and changes of direction, which are essential during critical moments of the game such as transitions, fast breaks, and defensive recoveries.[10,24] However, while this association is statistically significant, it is important to note that the practical significance of this 1.7% increase may be relatively small. The small effect size indicates that VHSE alone may not be a decisive factor in game outcomes, but rather one component of a broader performance profile.

Furthermore, while the AUC of 0.5736 in the multivariate logistic regression model indicates that the model performs better than random guessing (AUC = 0.5), it remains relatively modest in its ability to discriminate between wins and losses. This reflects the inherent complexity of game outcomes, which are likely influenced by numerous factors beyond GPS-derived metrics alone, such as psychological, tactical, and external conditions. The model's moderate discriminatory power further highlights the need for more comprehensive models that integrate a wider range of variables. As such, the coaching staff should interpret these multivariate regression findings contextually, considering VHSE as one of several performance indicators that, when combined with other tactical and physical factors, may contribute to this team's overall success.

There proved to be significant metric predictors when considered individually, as well. Univariate logistic regression models revealed the additional insight that Total Acceleration Load (TAL), Total Distance (TD), and Total Player Load (TPL) were significant predictors when considered individually, although their significance diminished in the multivariate context. This reduction suggests that while these metrics are important in understanding the key performance indicators of women's lacrosse, their impact may be intertwined with other performance factors, specifically VHSE. The relatively small Odds Ratios (ORs) in the univariate analysis—particularly those less than 1%—limit the practical significance of these predictors, reinforcing the need for a multivariate perspective to account for the interplay between various performance metrics.

These findings need to be compared with previous research. Our findings align with previous studies that have identified high-intensity efforts and overall player load as critical factors in athletic performance. Thornton et al. observed that high-intensity effort and distance contributed more to athlete load in games rather than practice in women's lacrosse, emphasizing the role of sprinting and intensive physical activity in competition.[25] These findings can be accentuated by Rosenberg et al's research on sprint zones, where they concluded that sprint zones 1-4, categorized by a percentage of maximum sprint speed (1=<60%, 2=60-69%, 3=70-79%, 4=80-89%), and distance zones 1-4 were all higher in games than during training for all positions, emphasizing the need for high-intensity efforts during competition and the need for being prepared for the demands of the sport.[26] The current study expands on this by providing a more detailed analysis across multiple seasons, highlighting specific GPS metrics that coaches can target to enhance player performance. It has been stated in previous literature that women's lacrosse athletes require very high levels of physical ability to excel in their sport. Emphasized by Calder et al. (2018), female lacrosse athletes tend to be in the 90% percentile for normative data according to American College of Sports Medicine (ACSM) and National Strength and Conditioning Association (NSCA) female guidelines.[10] This information is imperative as there has been found through multiple studies, including Calder et al's research, that there is an incredible demand for high-intensity bursts including accelerations, decelerations, and rapid change of direction in the sport of women's lacrosse.[10]

While the amount of sport science research for women's lacrosse is still in its infancy, there is a plethora of literature regarding other field sport athletes, including women's soccer. It has been found that women's lacrosse athletes exhibit comparable physiological characteristics to other sports including women's basketball, soccer, and track athletes, which is important to recognize in terms of developing sports performance and training programs.[23] Krustrup et al found interesting results that aerobic capacity discovered through the Yo-Yo IR1 test was correlated with the amount of high intensity running efforts elite female soccer players performed in competitive games.[27] This is important to note as the demands of these field-based sports, including the need for high-intensity efforts, lay in the foundation of physical preparedness.

While there is limited research in the field of performance-based measures for women's lacrosse athletes, it is important to recognize that there are now specific metrics that could be associated with team success. As the sport of women's lacrosse is continuously progressing, in terms of speed of play and formatting of the game, it is imperative to understand that women's lacrosse success is multi-factorial, meaning that success is due to many other components besides GPS metrics; however, this data does provide greater insight into the correlation between key performance indicators gathered during games and training to performance.[9] Recent game format changes to quarters rather than halves and the implementation of a shot clock help clarify the impact of these key performance indicators in game performance and that there are metrics that are important to track for sport scientists, including high-intensity efforts.[5,25]

Although the findings of this study provide valuable insights, several limitations must be acknowledged. Firstly, the data was collected over three seasons, which means there is potential overlap in athlete participation across these years. This overlap introduces dependencies within the data, as some athletes were involved in one to three seasons, potentially impacting the results. We did not control for this factor as the data was de-identified upon receipt, limiting our ability to account for within-subject correlations over time. Secondly, the study's scope was confined to a single NCAA Division I team (convenience sample), which may limit the generalizability of the findings to other teams or competitive levels. Thirdly, the analysis focused solely on GPS-derived metrics, excluding other potentially influential factors such as psychological variables, skill-related metrics, and physiological markers. Fourthly, although we acknowledge that some researchers have mentioned that Player Load is specific to the Catapult system and difficult to compare with other GPS systems, especially Thornton et al. concluding that an "all-in-one" variable (A1M) offers value to coaches in assessing athlete workload but is difficult to compare the measures to each other and other traditional variables, we chose to include this key performance indicator because Catapult GPS reports supporting more than 600 NCAA teams across the nation, and that more than 80% of Power 5 programs trust Catapult GPS.[25,28] A fifth limitation of this study is the lack of specific information regarding player roles (i.e., starter vs. bench player) or playing time. While the dataset provides detailed performance metrics, the absence of both role designation and playing time means that our analysis does not account for potential differences in performance metrics between starters/key players, bench players, and players with varying time on the field. This limits our ability to differentiate how much of the performance data reflects differences in game involvement or the influence of extended versus limited playing time. Moreover, while we acknowledge that GPS metrics such as VHSE are associated with winning games, there remains the possibility that they also reflect players' efforts to compensate in losing situations, such as chasing down opponents. These nuances were not captured in our analysis. Furthermore, the study analyzed repeated measures from athletes across multiple games and seasons, which introduces intra-subject correlations. While mixed-effects models could address this issue and provide more precise estimates, the current analysis used logistic regression to explore relationships between GPS metrics and game outcomes, given the exploratory nature of the study and the limitations of the de-identified dataset. Finally, the use of logistic regression, while suitable for the study's purpose, may not capture the full complexity of the relationships between performance metrics and game outcomes. Advanced analytical techniques, such as machine learning models, could potentially provide more nuanced insights.

In terms of implications of future research, the results of this study provide valuable insights into the specific demands of women's lacrosse, offering practical implications for training strategy and performance monitoring. Coaches and sport scientists may need to focus on improving VHSE through targeted training programs to find success in season. These findings also may emphasize the need for more comprehensive research into female athletes' performance metrics to develop sport-specific training regimens that enhance game outcomes. To enhance ROC values and thereby improve the model's discriminatory ability, future studies could investigate the incorporation of ensemble methods that combine multiple predictive models to refine accuracy and reliability. To build on these findings, future research should consider advanced analytical approaches, such as machine learning models (e.g., Random Forests, Gradient Boosting) to capture non-linear relationships and complex interactions between variables, potentially providing better predictive performance than logistic regression. Time-series analysis could explore performance trends over time, while clustering techniques could identify distinct performance patterns among players. Additionally, deeper analysis at the player and opponent level using mixed-effects models could provide further insights into individual and competitive dynamics. Incorporating more granular data, such as physiological factors, could also enhance understanding of performance determinants. Future studies should aim to include the distinction of player and playing time to enhance the granularity of the findings. Finally, expanding this research to include multiple teams and competition levels would improve the generalizability of the findings and provide a broader perspective on the key performance indicators in women's lacrosse.

This study identified Very High-Speed Efforts as a predictor of game outcomes in NCAA Division I women's lacrosse. This finding offers promising insights for optimizing training and game strategies, emphasizing the potential importance of high-intensity effort in competitive success. By monitoring these key performance metrics, coaches and sport scientists can potentially better prepare their athletes for the demands of high-level competition, ultimately enhancing team performance and success. Future research should aim to refine these models, incorporating a broader range of variables to fully capture the complexity of game outcomes in NCAA Division I women's lacrosse.

## Acknowledgements

We would like to express our sincere gratitude to Professor Kristi King (*kristi.king@louisville.edu*), for her invaluable support and guidance during the literature review phase of the preliminary idea.

(1) Catapult GPS *Total Player Load*. (2) Match Code = Loss/Win

## References

1. Mission and priorities. NCAA.org. Accessed July 15, 2024. https://www.ncaa.org/sports/2021/6/28/mission-and-priorities.aspx

2. U.S. women history. USA Lacrosse. Accessed June 27, 2024. https://www.usalacrosse.com/us-women-history

3. Women's lacrosse teams: a complete list. Accessed June 27, 2024. https://www.ncsasports.org/womens-lacrosse/colleges

4. Bobak J. The fastest game on two feet is introduced to GWU. *GW Hatchet.* Published 2023. Accessed July 15, 2024. https://www.gwhatchet.com

5. Calder AR, Duthie GM, Johnston RD, Engel HD. Physical demands of female collegiate lacrosse competition: whole-match and peak periods analysis. *Sport Sci Health.* 2021;17(1):103-109. https://doi.org/10.1007/s11332-020-00659-x

6. Zhu JW, Reed JL, Van Spall HGC. The underrepresentation of female athletes in sports research: considerations for cardiovascular health. *Eur Heart J.* 2022;43(17):1609-1611. https://doi.org/10.1093/eurheartj/ehab846

7. Smith ES, McKay AKA, Ackerman KE, et al. Methodology review: a protocol to audit the representation of female athletes in sports science and sports medicine research. *Int J Sport Nutr Exerc Metab.* 2022;32(2):114-127. https://doi.org/10.1123/ijsnem.2021-0257

8. Chambers R, Gabbett TJ, Cole MH, Beard A. The use of wearable microsensors to quantify sport-specific movements. *Sports Med.* 2015;45(7):1065-1081. https://doi.org/10.1007/s40279-015-0332-9

9. Bynum L, Snarr RL, Myers BJ, Bunn JA. Assessment of relationships between external load metrics and game performance in women's lacrosse. *Int J Exerc Sci.* 2022;15(6):488-497. https://doi.org/10.70252/OAWB5004

10. Calder AR. Physical profiling in lacrosse: a brief review. *Sport Sci Health.* 2018;14(3):475-483. https://doi.org/10.1007/s11332-018-0499-1

11. Vescovi JD, Brown TD, Murray TM. Descriptive characteristics of NCAA Division I women lacrosse players. *J Sci Med Sport.* 2007;10(5):334-340. https://doi.org/10.1016/j.jsams.2006.07.010

12. Kilian J. Activity profiling in NCAA Division I women's lacrosse. Concordia University Chicago; 2020. Accessed July 15, 2024. https://www.proquest.com/docview/2465486429

13. Devine NF, Hegedus EJ, Nguyen AD, Ford KR, Taylor JB. External match load in women's collegiate lacrosse. *J Strength Cond Res.* 2022;36(2):503-507. https://doi.org/10.1519/JSC.0000000000003451

14. Fields JB, Kuhlman NM, Jagim AR, Dulak-Sigler C, Jones MT. Analysis of accumulated workloads and performance testing across a collegiate women's lacrosse season. *J Strength Cond Res.* 2023;37(11):2213-2221. https://doi.org/10.1519/JSC.0000000000004551

15. Ransdell LB, Murray T, Gao Y, Jones P, Bycura D. A 4-year profile of game demands in elite women's Division I college basketball. *J Strength Cond Res.* 2020;34(3):632-638. https://doi.org/10.1519/JSC.0000000000003425

16. Acceleration load, acceleration density and acceleration density index. Catapult Support. Published November 17, 2022. Accessed June 27, 2024. https://support.catapultsports.com/hc/en-us/articles/360001559976-Acceleration-load-acceleration-density-and-acceleration-density-index

17. What is player load? Catapult Support. Published January 31, 2024. Accessed June 27, 2024. https://support.catapultsports.com/hc/en-us/articles/360000510795-What-is-Player-Load

18. Bunn JA, Reagor M, Myers BJ. An evaluation of internal and external workload metrics in games in women's collegiate lacrosse. *JSES.* 2022;6(1). https://doi.org/10.36905/jses.2022.01.02

19. Thornton AR, Figueroa Y, Davis P, Bunn JA. Comparison of game data between halves and quarters in Division I women's lacrosse. *J Sci Sport Exerc.* Published November 23, 2023. https://doi.org/10.1007/s42978-023-00260-x

20. Navalta JW, Stone WJ, Lyons TS. Ethical issues relating to scientific discovery in exercise science. *Int J Exerc Sci.* 2019;12(1):1-8. https://doi.org/10.70252/EYCD6235

21. Study quality assessment tools. National Heart, Lung, and Blood Institute. Accessed August 16, 2024. https://www.nhlbi.nih.gov/health-topics/study-quality-assessment-tools

22. James JJ, Klevenow EA, Atkinson MA, et al. Underrepresentation of women in exercise science and physiology research is associated with authorship gender. *J Appl Physiol.* 2023;135(4):932-942. https://doi.org/10.1152/japplphysiol.00377.2023

23. Enemark-Miller EA, Seegmiller JG, Rana SR. Physiological profile of women's lacrosse players. *J Strength Cond Res.* 2009;23(1):39. https://doi.org/10.1519/JSC.0b013e318185f07c

24. Lampros R, Sprague I. Return to sport following anterior cruciate ligament reconstruction: women's lacrosse. *J Women's Sports Med.* 2021;1(1):6-16. https://doi.org/10.53646/jwsm.v1i1.6

25. Thornton A, Neville B, Bunn J. Evaluation of athlete load and relationship between equation variables in Division I women's lacrosse. *J Sport Hum Perform.* 2024;12(1):1-7. https://doi.org/10.12922/jshp.v12i1.192

26. Rosenberg RC, Myers BJ, Bunn JA. Sprint and distance zone analysis by position of Division I women's lacrosse. *J Sport Hum Perform.* 2021;9(2):51-57. https://doi.org/10.12922/jshp.v9i2.175

27. Krustrup P, Mohr M, Ellingsgaard H, Bangsbo J. Physical demands during an elite female soccer game: importance of training status. *Med Sci Sports Exerc.* 2005;37(7):1242-1248. https://doi.org/10.1249/01.mss.0000170062.73981.94

28. Ambler W. NFL teams are all-in with Catapult, and here's why. Catapult. Published June 16, 2021. Accessed October 12, 2024. https://www.catapult.com/blog/nfl-teams-are-all-in-with-catapult-and-heres-why