

## **Introduction**

Basketball puts recurrent strain on the lower limbs, and even minor mechanical asymmetries can affect how athletes land, decelerate, and generate force. As a result, inter-limb asymmetry has become one of the most widely utilized predictors of injury risk. The widely used 10% threshold is based on rehabilitation and sports performance research that shows that when the weaker limb differs by more than 10%, athletes begin to exhibit measurable changes in movement patterns, reduced force absorption, and increased strain on the stronger limb (Parkinson et al., 2021; Fort-Vanmeerhaeghe et al., 2022). In other words, 10% is the threshold at which regular day-to-day variability ceases and biomechanically important imbalance begins.

However, this threshold is not universal. According to studies, asymmetry norms can vary based on the sport, position, testing method, or gender, implying that some groups may naturally tolerate slightly higher or lower levels of asymmetry. As a result, future research may require testing alternative criteria or doing sensitivity studies to establish how well the 10% limit suits basketball athletes, especially.

These concerns drive the core topic of this project: How does gender affect injury risk among basketball players with high asymmetry or acceleration-based workload? Understanding this link is critical for establishing whether existing screening criteria are sensitive enough for both male and female athletes.

## **Methods**

We focused on male and female collegiate basketball players ( $n = 214$ , classified; 161 with at least one metric available) using Stony Brook University's athlete-monitoring data. We considered the dataset to be longitudinal rather than a single time slice because each player had numerous data entries throughout the season. We classify each athlete using the most recent measurement available to guarantee consistency in comparisons. When data completeness varies over time, load-monitoring studies frequently use the "last available value" approach (Svilar & Jukić, 2018; Chan et al., 2024).

### **Metric 1: The Accumulated Acceleration Load (AAL)**

AAL is the sum of the instantaneous accelerations on the X, Y, and Z axes. It shows how much stress the muscles and nerves are under when speed and direction change quickly. These movements are very similar to the mechanical demands that come with being tired and at risk of injury in basketball(Svilar & Jukić, 2018; Luteberget & Spencer, 2017). Since AAL units are device-specific, we follow previous research and defined "high load" as the 90th percentile threshold (Frietas et al., 2025). Players who exceeded this threshold were marked for increased external effort.

## Metric 2: Maximum Force Asymmetry (LSI) Left-Right

The standard Limb Symmetry Index formula was used to calculate limb asymmetry:

$$LSI = \frac{\text{stronger limb} - \text{weaker limb}}{\text{stronger limb}} \times 100$$

We employed a 10% asymmetry threshold, which is generally acknowledged in the literature on injury risk and return to sport as a clinically significant cutoff (Parkinson et al., 2021; Kotsifaki et al., 2022). The data, however, suggests that threshold selection affects risk categorization and may underestimate neuromuscular impairments (Wellsandt et al., 2017). Future research should examine whether different cutoffs or sensitivity analyses better capture risk trends, even though our initial analysis employed the 10% criterion.

## Cleaning and Filtering Data

We eliminated:

- entries lacking force and acceleration information,
- unlikely values (such as incomplete acceleration logs or negative forces).
- The athlete-day records should be duplicated.

Each athlete contributed a single, comprehensible data point to the risk-category classification thanks to this technique.

## Classification of Risk

Using the two previously stated thresholds, athletes were allocated to:

- Minimal danger (below both bounds).
- Elevated asymmetry ( $\geq 10\%$  LSI only)
- Load at or above the 90th percentile is referred to as high load.
- Combined Risk (both are elevated).

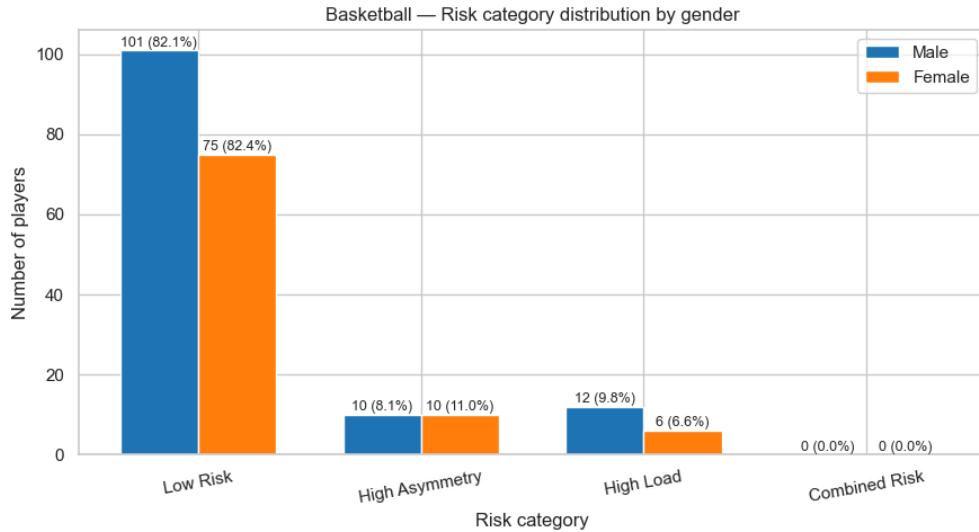
The gender-based risk distributions represent longitudinal data summarized at the most recent accessible time point rather than a one-day snapshot because the dataset contained multiple time points but classification depended on each athlete's final measurement.

## Results

A cohort of 214 basketball players (91 females, 123 males) was evaluated for injury risk profiles using bilateral force asymmetry and accumulated acceleration load as primary indicators. Players were stratified into four mutually exclusive risk categories: Low Risk, High Asymmetry, High Load, and Combined Risk.

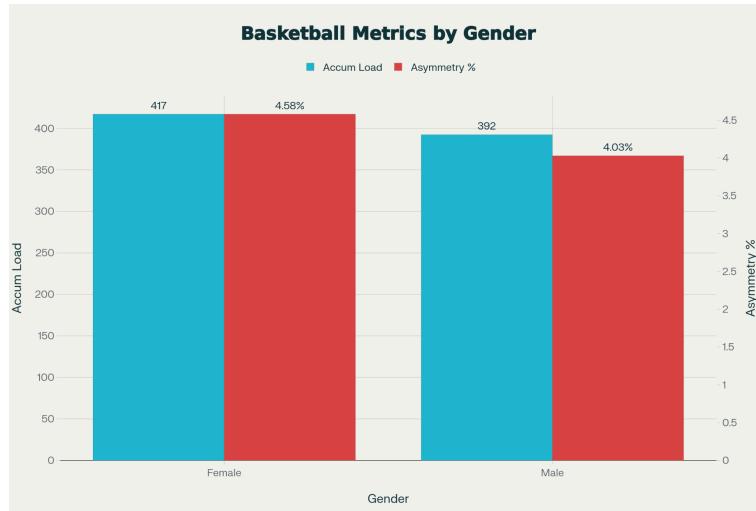
From the data, low risk dominated the cohort, comprising 176 players (82.2%; 75 females, 101 males). This means that they exhibit both  $<10\%$  asymmetry and load values below the basketball-specific 90th percentile (662.53). High Asymmetry was observed in 20 players (9.3% overall; 11.0% of females [10/91] vs. 8.1% of males [10/123]). High Load affected 18 players

(8.4% overall; 6.6% of females [6/91] vs. 9.8% of males [12/123]). Combined Risk was absent (0%; 0/214).



**Figure 1: Risk Category Distribution**

Gender differences within these categories were modest. High Asymmetry prevalence was slightly higher among females (11.0%) than males (8.1%), whereas High Load prevalence was higher in males (9.8%) than females (6.6%). A chi-square test indicated no significant association between gender and risk-category distribution ( $\chi^2 = 1.389$ ,  $df = 2$ ,  $p = .499$ ), with negligible effect size (Cramér's  $V = 0.081$ )



**Figure 2: Metrics Prevalence Level**

No athletes met the criteria for Combined Risk in this sample. Aggregating multiple dimensions into a single composite risk designation is conceptually meaningful because injury risk is often multifactorial and can escalate when independent risk factors co-occur. However,

multidimensional indices also require careful interpretation: high values in one domain may offset or mask risk in another. In this analysis, potential conflicts were handled by classifying athletes based on the *presence* of threshold exceedances in each domain, rather than averaging or weighting domains. This approach avoids diluting meaningful risk signals and provides clearer guidance for targeted intervention. The absence of Combined Risk cases may reflect effective load management practices, natural self-regulation by asymmetrical athletes, or the statistical rarity of meeting two independent thresholds simultaneously.

In summary, this basketball cohort exhibited a highly favourable injury-risk profile, with more than 80% of athletes demonstrating acceptable bilateral symmetry and moderate cumulative load, and no athletes presenting the most dangerous combination of deficits. Nevertheless, the “Low Risk” designation should be interpreted cautiously, as the absence of elevation in these two markers does not guarantee injury-free status. Targeted, individualised interventions for the approximately 18% of athletes in single-domain high-risk categories, combined with ongoing monitoring, are recommended to maintain and, if possible, improve this low-risk majority.

## Discussion

The results of this study are a growing body of evidence examining external workload and limb asymmetry as warning signs of musculoskeletal injuries in basketball players. The majority of athletes showed asymmetry values below the frequently cited 10% threshold, which is usually regarded as biomechanically acceptable for healthy team-sport athletes, in line with earlier research (Parkinson et al., 2021). According to studies showing moderate-to-high but manageable workloads in competitive situations, cumulative acceleration loads also fell within expected values for collegiate basketball throughout the season (Djaoui, L. et al., 2017). Therefore, the high percentage of Low-Risk athletes (>80%) supports the current understanding that well-managed training environments typically result in biomechanical profiles that are generally stable.

Our analysis also filled a significant gap in the literature by examining whether gender differences affect risk classifications when asymmetry and load are simultaneously considered. The current dataset showed no significant correlation between gender and the distribution of risk categories, despite earlier research revealing sex-specific differences in landing mechanics, knee valgus, fatigue responses, and neuromuscular control (Baugh et al., 2018). This implies that while gender can affect biomechanics, these variations may not be detectable in these metrics, or the thresholds may not be sensitive enough to identify them.

More importantly, a Low-Risk label should not be taken to mean “no risk”. These athletes still face regular training loads that carry an inherent risk of injury, but they did not exceed the thresholds used in this study. So “low risk” refers to relatively lower exposure in this dataset rather than a lack of significant harm risk. According to Bittencourt et al. (2020), this explanation

supports the growing understanding that risk is an ongoing process and that simplified labels may oversimplify complex neuromuscular data.

In terms of application, the results support the use of tailored performance-flag systems(green, yellow, red). Monthly variations in accumulated load, peak forces, and asymmetry provide coaches and athletic trainers with valuable information, even in the absence of high-risk values. For instance, a slight increase in asymmetry may warrant active monitoring or adjustments to recovery, especially among female athletes. Athlete-monitoring systems can identify these acute–chronic imbalances before injuries occur, according to a recent study, and early workload shifts may signal an increased risk of injury. (Bache-Mathiesen et al., 2023). The key takeaway is not to wait for both flags to appear together to intervene.

## **Limitations & Future Directions**

When evaluating the results, it is essential to note the many limitations of this project. First, the training-load timeline's accuracy was affected by incomplete or missing data in the dataset, especially during some months. Incomplete uploaded data might cause these variations, irregular testing schedules, or device failures, all of which may affect load increase detection or hide real risk patterns.

The risk classification criteria used were another limitation. These cutoffs may not accurately reflect the ideal criteria for risk assessment specific to basketball or gender, as they were obtained from generic biomechanical standards. Individualized thresholds based on an athlete's past performance may be more sensitive for early risk identification. (Ibáñez, S., et al., 2022; Malone, S., et al., 2020)

Only a portion of the complex nature of injury risk is represented in the dataset, which includes accumulated acceleration load, peak propulsive force, jump height measurements, and left/right max force. Injury risk is greatly affected by factors such as hormonal fluctuations, past injury history, sleep, psychological stress, and seasonal weariness, all of which were not available. (Wang C. et al., 2024; Fulton J. et al., 2014; Fort-Vanmeirhaeghe, A. et al., 2025; Gao, B. et al., 2019).

Future studies should include larger, more diverse athlete groups to assess gender-specific loading patterns better. More advanced risk modeling and the ability to identify tiny shifts over time would be possible with longitudinal data containing fewer missing months. A more thorough risk-profile model that accurately reflects the complex nature of injury risk could be developed by adding variables such as fatigue evaluations, hormonal variations, injury records, and GPS monitoring.

Also, it may be possible to accurately reflect differences in biomechanical sensitivity by using different or personalized thresholds, such as sex-specific cutoffs or z-score-based tailored limits. Athlete-specific baselines help develop tailored intervention plans and more accurately detect early changes. Coaches may be able to better identify dangers over time by including these customized measures into automated flag systems within athlete-monitoring platforms.

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