Visualizing Risk Factors and Career Impacts of Injuries Among MLB Pitchers

Team 73 - Sumair Shah, Sejal Dua, Tim Ehlenbeck, Jake Hlavaty, Leon Hu, Matthew Schulz

1 INTRODUCTION

In Major League Baseball (MLB), pitchers hold a pivotal role, often commanding top salaries and comprising nearly half of all roster spots. Despite their importance, injuries plague pitchers, with a staggering 39% of professional baseball injuries attributed to them [13]. Despite existing research efforts and clinical studies, the prevalence of career-altering injuries has remained alarmingly high, and the impacts of these injuries on future performance is not well defined. Professional baseball teams currently rely upon sparse internal datasets, retrospective analysis, and generalized player health protocols to inform rest, load management, and training decisions. However, without joining disparate data sources including baseball statistics, workload, and injury data, the insights into the factors that drive pitcher injuries remain sparse or inconclusive.

2 PROBLEM STATEMENT

Our research aims to delve into the intricate web of factors surrounding pitcher injuries in MLB. The lack of effective injury mitigation strategies motivates a need to harness advanced analytics and pitch tracking technologies to identify and quantify the factors most correlated with injuries. By uncovering the quantitative relationships between pitching mechanics, workload, and injury incidence, we aim to offer actionable recommendations for mitigating injury risk and enhancing player longevity in MLB. The findings of this analysis could unlock value for general managers, team personnel, players, and fans by contributing to a deeper understanding of pitcher injuries from various lenses.

3 LITERATURE SURVEY

(1) *Injury Prevalence, Trends and Risk Factors*: Baseball injuries have risen over the past few decades, especially for pitchers [6][7]. Injury risk starts at the youth level where players may pitch without limits and on consecutive days [1]. Among elite Korean youth players, where players practice far more than in other countries, 82.7% of players had experienced at least one injury and average 1.9 injuries by age 16. Injuries to the lower back and elbow were common, and similar injury locations were also observed at the professional level [9]. It is proven that players who throw more pitches are more likely to experience these styles of injuries at all levels of play [18]. The abbreviated training schedule of the 2020 Major League Baseball season further exposed these problems, as pitchers were over three times more likely to experience elbow injury [16]. Our project will focus on these common injury types and work towards identifying safe pitching standards at all levels of play to break the upward trend of injuries.

(2) *Impactful Injuries Among Professional Pitchers*: UCL injuries often require season-ending surgery, and are often attributed to overuse during developing years [23]. Lower back injuries associated with hamstring injuries can resurface and should be approached with caution [2]. The number of players inactive due to disability has sharply increased since the early 2000s [7]. Team spending and medical advances have had a minimal impact on the frequency of injury [22]. We will focus on these key injuries to identify new ways to identify them and lower the number of days a pitcher is on DL.

(3) *Predicting Injury*: Prior research has examined modifiable and non-modifiable factors to predict expected time lost to injury [3]. Physical screenings of high school pitchers showed no correlation between preseason range of movement and injury frequency [19]. Studies have indicated that pitchers see a sharp increase in velocity on their fastball as they approach a UCL tear [10]. Pitchers with higher average velocities appear more likely to experience UCL tears, but additional investigation is needed [5]. By introducing additional data sources we aim to discover new ways to identify injuries and decrease impact.

(4) *Returning from Injury*: Reviewed studies focused on return to play from UCL surgery. A majority of the subjects returned to similar levels of performance post-surgery [4][15]. Post-surgery innings and pitch counts did not significantly impact the likelihood of requiring revision surgery [8]. However, if revision surgery is necessary, the player

may face a lower return-to-play rate, compared to the first surgery [14]. Often players are rushed back from injury and stats may prove helpful to identify players earlier who are at risk of re-injury.
(5) *Evaluating the Impact*: Performance evaluation post-injury is an integral part of our project, and defining performance itself will be key. Predicting team performance without injuries was previously attempted without success[12]. Past studies evaluating player performance using simpler metrics like pitching velocity [11] are outdated with the increasing availability of advanced tracking [13][17]. Modern advancements in data collection should allow a more comprehensive evaluation of injury impact when modeled.
(6) *Injury Risk Mitigation*: Baseball franchises have a significant interest in mitigating injury risk due to their significant financial impacts. Current injury prevention strategies in youth baseball emphasize mechanics and workload management to prevent overuse [17]. Research indicates that increased double headers, as seen in the pandemic-affected 2020 season, correlate with higher injury rates per 1000 exposures [22][23]. However, existing workload studies often lack specificity across player positions. For example, the Acute to Chronic Workload Ratio (ACWR) assesses weekly game counts relative to four-week training averages. However, instead of analyzing usage in terms of game appearances, more research is needed to identify which quantifiable load metrics can serve as the most effective proxy for injury risk.

4 PROPOSED METHOD

Acute to Chronic Workload Ratio (ACWR) is the current state-of-the-art method for measuring injury risk in the professional sports player health space [21]. We will build upon the concept of Acute to Chronic Workload Ratio, but define it specifically for pitchers using metrics relevant to their throwing mechanics. Further, we will aim to tie player injuries to sharp changes in acute workload and provide tangible evidence of player workload mismanagement using detailed tracking data, which was unavailable prior to 2018.

4.1 Data Acquisition

(1) **Injury data**: Injury data for the 2018 through 2023 MLB seasons was obtained from FanGraphs (https://www.fangraphs.com/), a publically available source.
(2) **Pitch Tracking Data**: Pitch data for the 2018 through 2023 seasons was obtained from the R package `baseballr` [20], which consolidates data for free from sources like fangraphs.com, baseball-reference.com, and baseballsavant.mlb.com. We are using this data to evaluate player workload and performance.
(3) **Game and Weather Characteristic**: Utilizing a publicly available API provided by MLB.com, we matched player injuries to factors such as weather, start time, temperature, and game duration to give a further glimpse into any possible game time scenarios that may have lead to injury.
(4) **Player Biological Information**: We used the industry standard Chadwick Baseball Bureau database accessible through the R package `baseballr` [20] to acquire player birthday and pro debut dates, in order to examine the effects of age and experience.

Since our resulting datasets had a size of approximately 2.41 GB on a local disk, data was stored and hosted in an Azure SQL database for analysis. The final interactive visualization took the form of a Tableau dashboard, through which an extract database was created such that connectivity to the backend database was not required.

One complication was that our two disparate data sources were not acquired through the same provider. For this reason, player IDs could not be used to join the datasets. Our solution was to perform a string-based crosswalk, matching the datasets on pitcher names with a success rate of approximately 95%. Data sources (1) and (2) were utilized in the backend powering our visualizations while sources (3) and (4) were utilized in the exploratory data analysis phase of this research.

4.2 Innovative Methodology

We propose a modified ACWR specifically for pitchers, denoted as pACWR. This will be calculated as the ratio between two workload metrics representing:

(1) Acute Workload: Defined as the average *pitching load** in the most recent week (e.g., last 7 days).

(2) Chronic Workload: Defined as the average *pitching load** thrown (or innings pitched) over a longer period representing chronic training load (e.g., previous 4 weeks).

Pitching load denotes a metric we will define using analytical experiments and statistical testing in section* **??. *If a particular workload measure demonstrates significant spike at the time of injury, we will we use it to define load in the rest of our analysis.*

We were unable to find existing research that attributed professional pitcher injuries to statistical workload change in the period leading up to injury. Our project will be innovative purely due to the lack of rigorous analysis being preformed by anyone publicly when it comes to workload from a quantitative lens.

4.3 Derivation of Novel Metric

As mentioned in section 4.2, rigorous statistical testing was performed to identify the best proxy for pitcher training load, to be used in our pACWR formula. Candidate metrics included pitch count, release spin rate, release speed, batters faced, and others that were broken out by the speed and spin rate of various pitch types.

4.3.1 Specificity Analysis. Descriptive analytics were performed to compare and contrast the candidate metrics. Our findings are summarized in Table 1.

Table 1: Summary Statistics for Pitch Load Metrics

Pitch Load Metric	μ_{ACWR}	σ_{ACWR}	Outliers
Pitch Count	0.31	0.03	20%
Release Speed (FB)	0.48	0.11	50%
Release Speed (BB)	0.61	0.06	30%
Release Spin (FB)	0.49	0.09	40%
Release Spin (BB)	0.55	0.07	25%

Given that the objective of this metric is to detect anomalous patterns in the data, we analyzed how many observations lied outside of the interquartile range. Due to its stability and high specificity, Table 1 suggests that pitch count is the best metric for our definition.

4.3.2 Correlational Analysis. To further assess candidate metrics, correlations were visually and quantitatively examined. As shown in the Figure 1, the definition

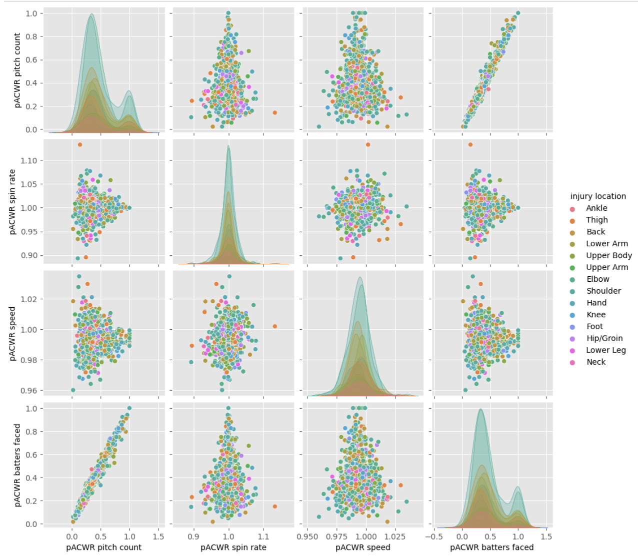

Figure 1: Pair plot depicting correlations between candidate pACWR metrics

of pACWR which uses pitch count as the load indicator was highly correlated with the definition that uses batters faced. Pitch count pACWR is advantageous to batters faced pACWR because pitch count is more granular and is less dependent on the pitcher's efficiency on the mound. Speed and spin rate did not yield promising findings with respect to this metric because of the noisy signal (i.e., increased variance) caused by different pitch types. The final step was to validate the statistical significant of using pitch count as our workload metric.

4.3.3 Statistical Testing. A Welch's t-test was performed to compare workload at the time of injury with typical workloads. More specifically, the two sample groups used for the test were average player workloads (pACWR) in the 7 days leading up to injury and player workloads not in the 7 days leading up to injury. A Welch's t-test was performed because the sample populations did not have equal variance. This statistical test was implemented in Python using the `scipy` library.

In statistical terms, the null hypothesis for this test is that acute to chronic workload does not play a significant role in injuries. Since the Welch's t-test yielded a p-value of 0.0003798 (<0.05), we can reject the null hypothesis. In other words, there is strong evidence that the workload at the time of injury is different from typical workloads. This suggests that workload should be a primary focus in future injury mitigation efforts and other injury-related analyses.

4.3.4 Summary of pACWR Approach. To conclude the technical derivation of our novel workload metric, pitch count was selected as the load metric in the computation of pACWR for the following reasons:

(1) Table 1 shows that pACWR using pitch count yields a tighter variance and less outliers.
(2) Figure 1 suggests that pACWR is correlated with batters faced but not correlated with speed and spin rate.
(3) The Welch's t-test yielded significant results suggesting that workload (pACWR) around the time of injury varies significantly from typical workloads.
(4) In the spirit of democratizing access to the insights gleaned form this study, pitch count enables baseball players at all levels to manage their workload. It also enables players to manage their workload outside of the context of pitches in practice contexts, whereas speed and spin rate require high-cost, data sensing infrastructure that likely is only accessable following official MLB games.

$$pACWR = \frac{\text{pitch count in preceding 7 days}}{\text{pitch count in preceding 28 days}} \quad (1)$$

The following sections will present analyses and visualizations incorporating our pACWR metric (defined simply in equation 1). For context, a pACWR value of 0.25 is considered normal workload because it would suggest that an MLB pitcher's usage in the preceding one week is proportional to his usage in the preceding four weeks. Values above this threshold are indicators of increased load. Generally, periods of load fluctuation are hypothesized to be correlated with increased injury incidence.

4.4 Analytical Approach

Through our analysis and visualization, we plan to leverage pACWR through the following set of experiments:

(1) pACWR at Injury: We will calculate pACWR for each pitcher placed on the injured list (IL) during the 2019 through 2023 seasons.
(2) Injury Rates: We will calculate injury incidence rates per 1000 player exposures [22]. Player exposure will be defined as one game played by a pitcher.
(3) Performance Changes Following Return: We will analyze advanced pitch tracking data to measure any identify pitching performance changes seen, in the period leading up to major injury and after the player's recovery and return.
(4) Subgroup Analysis: We will perform subgroup analysis to compare injury rates and pACWR between different pitcher types (e.g., starters, relievers) as will as between injury types (e.g., surgery vs strain or elbow vs shoulder). Injury types are a categorical data type that can get very granular, so we will bucket them into more generic labels to avoid data sparsity issues.

5 EXPERIMENTS AND EVALUATION

5.1 Hypothesis Evaluation

We evaluated high level trends across the dataset to see if there are correlations that should be accounted for in our metric. No clear relationship was uncovered between weather and injury incidence. Travel distance also showed no significant link to pitcher injury rates.

We observed that injury incidence increases monotonically over the course of a regular season, reaching a maximum at month eight, the start of postseason playoffs. The data supported the rather intuitive hypothesis that poorly performing teams which do not qualify for playoffs should incur fewer injuries. The two teams with the fewest injuries have only appeared in one postseason since 2020, whereas the two teams with the highest number of injuries have appeared in all postseasons within our time period of interest.

Our hypothesis that older players would be more at risk proved to be untrue as the distribution of injury incidence by player age almost exactly matches the player age distribution in the MLB. Two other factors we examined, weather and game start time, also exhibited no discernible effect on injury occurrence.

The hypothesis that yielded meaningful insights and served as the basis of our analysis and pACWR was the risk of changing pitcher workload throughout the season. Prior to injury, we often see a dramatic shift in workload compared to the chronic baseline that seems to aggravate many arm-related injuries, including the devastating and season-ending Ulnar Collateral Ligament (UCL) tear.

5.2 Subgroup Analysis

In section 4.4, we propose several experiments to implement, relating to pACWR. Our interactive tableau dashboard presented in 5.3 addresses experiments (1), (2), and (3): pACWR leading up to injury and injury incidence. For experiment (4), the subgroup analysis, a programmatic approach was used to uncover insights.

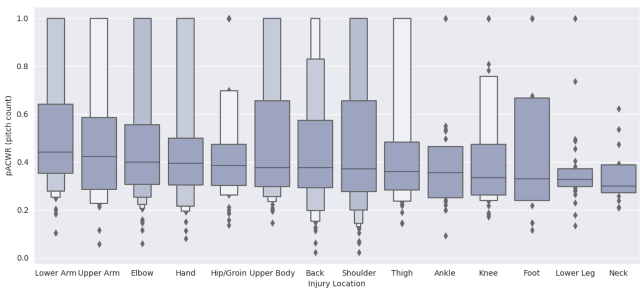

Figure 2: Boxplot depicting pACWR by injury location at the time of injury

Figure 2 shows the distribution of pACWR at the time of injury, broken out by injury location. Arm, elbow, and hand injuries are found to have the highest average pACWR at the time of injury, as compared to other injury locations. The variances of pACWR for these specific locations is also wider, which may suggest that there are relatively more instances of injuries caused by under-use. Lower leg, foot, and knee injuries are not characterized by consistently higher pACWR values at the time of injury. A similar approach found that relievers tend to have a higher average pACWR at the time of injury as compared to starting pitchers.

5.3 User Interface

To accompany all of our insights, we have created an interactive visualization hosted on Tableau Public which allows users to explore specific players and injuries in additional detail.

The Tableau visualization is composed of two views encompassing several filterable sheets:

(1) **Injury Trends and Recovery Time**: A temporal view enabling users to visualize injuries per game by month and average recovery time by injury type.

(2) **Pitcher Performance and Workload Pre- and Post-Injury**: A view that allows the user to select a pitcher who got injured, see their workload leading up to their injury, and visualize performance metrics pre- and post-injury. This visualization, if explored in detail, could offer insights into how pitch type distribution, speed, and spin rate may have been early markers or drivers of injury.

In this section, we will discuss how some of the views can unlock insight within our visualization. Figure 3 shows an example of Shane Baz, a player who tore his UCL on July 13th, 2022. There is a clear indication of change in pAWCR as we see a 60% dip approaching injury. The remainder of the view gives a breakdown of pitching tendencies and metrics before injury to indicate possible causes.

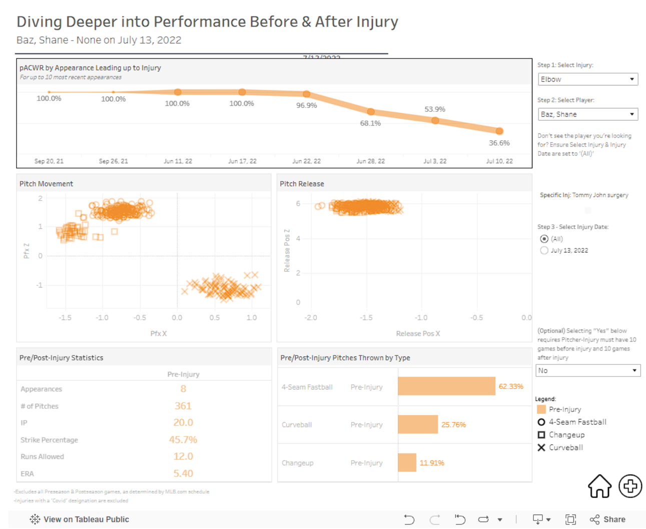

Figure 3: Shane Baz dashboard view prior to elbow injury in 2022

Shane has not yet returned form injury due to its severity, but for players who have returned, such as Tyler Glasnow, the user can compare performance metrics before and after injury. Figure 4 shows an analysis of pAWCR alongside a plot of pitch movement, release position and other statistics before (in orange) and after injury (in blue). This view enables users to see how a pitcher's release speed, usage, strike percentage, runs allowed, and general pitch arsenal may have been affected by the injury. The pitch movement plot in the given example shows a decrease in curveball movement post-surgery, a finding that may be further analyzed for actionable insights during a player's recovery.

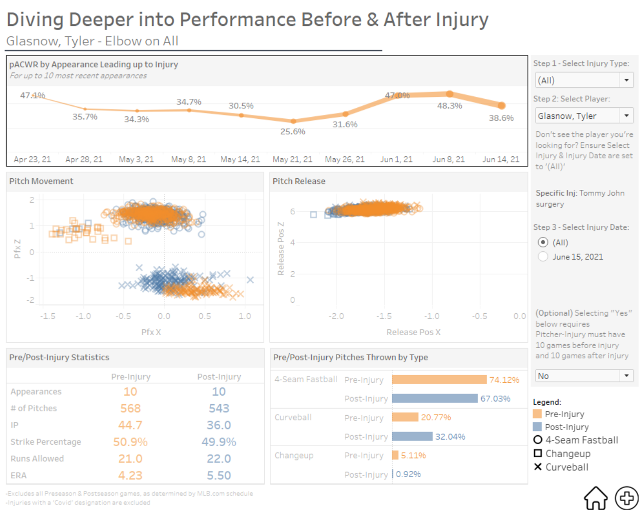

Figure 4: Pre- and post-injury dashboard for pitcher Tyler Glasnow

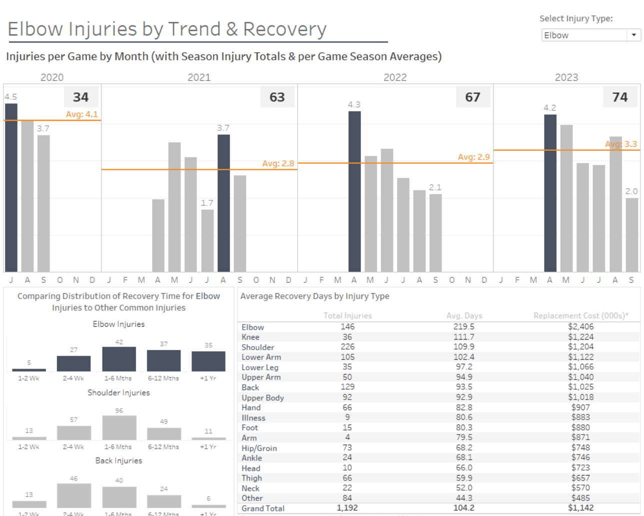

Figure 5: Elbow injury breakdown from 2022 through 2023

Figure 5 provides additional summarized views of elbow injuries specifically due to their severity and recent propensity. Interestingly, we do see overall injuries going down over the last few seasons but a steady increase in elbow injuries per month over the last few seasons. Elbow injuries, are often much more extreme and can be season-ending, so although it appears teams are trending towards better conditioning and daily management, pitchers are asking more of themselves than their body can tolerate. The recovery time plots indicate that arm and elbow injuries often have much longer recovery times and also are the most costly injuries without accounting for contract wages lost.

6 DISCUSSION

The primary advantage of pACWR is that it flags both over-use and under-use injury risk. Injuries that occur near the start of any given season (i.e. pACWR is 1) are suspected to be due to the player not having enough game-like conditioning or "ramp up" prior to putting their body through intense load. On the other hand, a 200% increase in usage over a given week would cause pACWR to spike to around 0.5, which is also an indicator of injury risk. The hypothesis that periods of load fluctuation are correlated with increased injury incidence was validated.

Though most injuries are seen to be associated with changes in workload, defining a safe workload level in the future looks different for each pitcher depending on role and individual style. That said, our aggregate analysis revealed an actionable insight for baseball teams and players. For load management purposes, a pACWR value of 0.44 is the threshold at which pitchers are at high risk of injury.

While this study yielded actionable insight, there were several limitations and obstacles worth mentioning. First, injury analysis is always more robust with increased data availability. For example, if pitch count in practice was incorporated prior to the start of the season, this would enable a more detailed examination into early season injuries which, in our study, had a pACWR value of 1. Additionally, future pitcher load studies might consider deriving a more involved pACWR definition. For example, pACWR could be computed as a weighted average of normalized speed and spin rates by pitch type.

Lastly, some potential future extensions of this project include a more in-depth analysis into whether players can truly return to peak performance following injury, how to mitigate the risk of re-injury, analyzing the effects of travel-related fatigue on injury risk, and more.

All team members have contributed a similar amount of effort.

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