SHOULDER AND ELBOW INJURY RISK IN PROFESSIONAL BASEBALL PITCHERS

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STATEMENT OF ORIGINALITY

I certify that the intellectual content of this thesis is the product of my own work and that all the assistance received in preparing this thesis and sources have been acknowledged.

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Lachlan James Hodge

ACKNOWLEDGEMENT OF COUNTRY

I would like to acknowledge the traditional owners of the land on which the research activities pertinent to this thesis were conducted, the Gadigal people of the Eora nation.

I would also like to pay my respects to Elders past and present and extend my gratitude for the privilege of inhabiting the land that is so sacred to them and their people.

STUDENT DECLARATION

This thesis was completed for the Master's degree by Research and has not been submitted for a higher degree or diploma in any other University or academic institution. I hereby declare that this thesis is my own work and that, to the best of my knowledge and belief, it contains no material from any other source, except where due acknowledgement is made. I also acknowledge that if my candidature is successful, this thesis will be lodged with the University Librarian and made available for immediate public use.

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AE	=	Athlete Exposures
AUPRC	=	Area Under Precision-Recall Curve
CV	=	Cross Validation
DAG		Directed acyclic graph
dASI	=	Directional Asymmetry Index
DOM	=	Dominant
ER	=	External Rotation
FLEX	=	Flexion
FP	=	False Positives
GAMM	=	Generalised Additive Mixed Model
GERD	=	Glenohumeral External Rotation Deficit
GIRD	=	Glenohumeral Internal Rotation Deficit

GLMM	=	Generalised Linear Mixed Model
HITS	=	Health and Injury Tracking System
HT	=	Humeral Torsion
IL	=	Injured List
IR	=	Internal Rotation
LMER	=	Linear Mixed Effects Regression Model
LOA	=	Limits of Agreement
MER	=	Maximum External Rotation
MiLB	=	Minor League Baseball
MLB	=	Major League Baseball
m/s	=	Meters Per Second
MPH	=	Miles Per Hour
MRI	=	Magnetic Resonance Imaging
MVIC	=	Maximal voluntary isometric contraction
NDOM	=	Non-dominant
RMSE		Residual Mean Squared Error
ROC	=	Receiver Operator Characteristic
ROM	=	Range of Motion
SLAP	=	Superior Labrum Anterior-Posterior
SSC	=	Stretch-shortening Cycle
TP	=	True Positives
TR	=	Total Rotational
UCL	=	Ulnar Collateral Ligament

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CHAPTER 1: INTRODUCTION

Baseball is a sport that is played across the world, with significant roots in the United States, Latin America, and Asia. Major League Baseball (MLB) is the premier professional baseball league in the world and has affiliates in the United States and Canada. MLB reportedly exceeded $US10 billion in revenue in 2017, with 15 consecutive years of record-breaking revenue from the years 2003 to 2017. With the significant financial stakes involved in MLB, it is imperative to field the most talented players as often as possible to attract consistent crowds and a winning culture for the team.

The pitcher plays a crucial role in baseball, acting as the cornerstone of a team's defensive capacity. A talented pitcher could significantly limit the run-scoring potential of opposing teams, greatly enhancing their own team's chances of winning the game. However, due to their high throwing volumes, pitchers are more susceptible to arm injuries compared to other players in the team. This issue has led to ongoing debate regarding the which variables are most associated with shoulder and elbow injury risk in professional baseball pitchers.

This thesis aims to address some of the key deficiencies in the scientific literature by:

1. Summarising the current literature on shoulder and elbow injuries and their associated risk modifiers in professional baseball pitchers.
2. Developing a generalized additive mixed model alongside a linear mixed effects regression model to predict humeral torsion and determine their performance error compared to a null model, along with the standard error of ultrasound when performing this assessment.
3. Developing a generalized additive mixed model using preseason shoulder rotational range of motion measures and various demographic data as predictor variables to predict injury in the upcoming season.

The five chapters of this thesis are designed to answer the aims stated above.

In Chapter 1, the reader is introduced to the topic and provided a rationale and overview for this thesis.

In Chapter 2, an integrated narrative review of the published literature is formed that investigates shoulder and elbow injuries and their risk modifiers in professional baseball pitchers. The Chapter begins with a brief overview of baseball pitching biomechanics and the resulting adaptations to the pitcher's throwing shoulder. Following that, an outline is given of the burden of the most common pathologies seen by clinicians and researchers, along with their impact and severity. Lastly, this Chapter discusses the shortcomings of the current methods associated with injury risk modifier identification in baseball and provide the rationale for the statistical methods used in Chapter 4.

In Chapter 3, the focus shifts to humeral torsion. Humeral torsion is an identified injury risk modifier in baseball pitchers and is more difficult to measure than other injury risk modifiers. Thus, Chapter 3 is an attempt at using a generalised additive mixed model to predict humeral torsion in professional baseball pitchers using modifiable and non-modifiable predictor variables. These predictor variables consist of shoulder range of motion measures and other demographic variables including age, height, and continent of origin.

Chapter 4 consists of a retrospective analysis investigating shoulder and elbow injuries in professional baseball pitchers for one MLB affiliate over the course of 10 years. A generalized additive mixed model was developed using rotational range of motion measures of the shoulder as predictors taken during preseason athlete screening. The predictor variables were then assessed for their importance in the predictive model, allowing the reader to gain insight into their individual impact on injury risk.

Finally, Chapter 5 summarises the findings from the existing literature and this thesis, and further discusses our ability to detect and predict humeral torsion, as well as those at a greater risk of shoulder or elbow injury in their upcoming season.

The body of research within this document furthers our understanding of injury risk in professional baseball pitchers and advances the current paradigm in injury risk analysis in baseball to a more sophisticated, multivariate predictive modelling approach.

CHAPTER 2: SHOULDER AND ELBOW INJURIES IN BASEBALL PITCHERS: AN INTEGRATIVE, NARRATIVE REVIEW OF THE LITERATURE

2.1. Introduction

The baseball pitch is a ballistic movement that involves a complex and synchronous series of movements. The primary goal of a baseball pitcher is to throw the ball at high velocity with considerable accuracy to compel the batter to either swing and miss, or to make weak contact with the ball. In order to impart enough momentum behind the ball and achieve this goal, biomechanical analysis has shown that the shoulder and elbow undergo extreme positional changes within a short amount of time. The average amount of time between the instant when the front foot contacts the ground and ball release has been measured at approximately 145 ms.[1] This short duration results in the internal rotation velocity of the shoulder reaching upward of 7,500-7700 degrees per second (one of the fastest human movements on record), thereby conveying a tremendous amount of force through the shoulder, elbow, wrist, and hand.[2,3]

Shoulder and elbow injuries to professional baseball pitchers are an ongoing concern, costing professional baseball organizations hundreds of millions of dollars each year to replace injured players, in addition to the impact of losing a talented player from their roster.[4] The cause of the rise in injuries is difficult to discern, however it comes at a time when pitching velocities, and the consequent musculoskeletal demands of this, are also at an all-time high. Since 2015, the average fastball velocity in MLB has risen by 0.8 MPH (0.358 m/s) to 93.2 MPH.[5] The temporal increase in pitching velocity can be further exemplified when individual changes are considered. For example, in 2023 there are currently 11 pitchers with an average fastball velocity higher than the 2015 peak of 98.0 MPH, including a 3.9 MPH increase in the peak value to 101.9 MPH[5]. Efforts to reduce injuries in professional baseball have mostly consisted of screening athletes during the team's preseason. Athlete screening in baseball typically consists of various anthropometric, range of motion and strength measures to assess a player's risk of injury in the upcoming season.[6] As this Chapter will argue, determining which athletes are at higher risk in baseball screening has proven to be difficult due to the functional adaptations that occur within the baseball pitchers shoulder from the forces associated with repetitive pitching. Thus, there is ongoing debate in the literature as to which measures are most important to measure, and what they are telling us about injury risk.

To contextualise the current state of preseason screening for injury risk in baseball pitchers, this review of the literature aims to:

1. Outline the adaptations that occur in the shoulder and elbow of baseball pitchers as they relate to the biomechanics of pitching.
2. Outline the burden of shoulder and elbow injuries in professional baseball pitchers and summarize the current literature investigating risk markers for shoulder and elbow injuries.
3. Discuss injury risk marker identification in throwing athletes and novel methods of ascertaining injury risk with potential application in baseball.

2.2. Adaptations in the Shoulder and Elbow Through the Lens of the Biomechanics of Pitching

Baseball pitching is a complex movement that requires a tremendous amount of force to be transferred from the lower body, through the trunk, and into the upper extremity of the athlete.[7] The measurement of the angular velocities and timing of this sequencing is performed by biomechanical analysis, typically in the form of force plates and 3-dimentional motion capture cameras.[8] The increase in hardware and software capabilities in recent years has brought with it an increase in the sophistication of biomechanical analysis in the baseball pitch.[9]

There is significant overlap in the foundational concepts and principles that have been established over the last 4 decades, which have remained mostly unchanged.[9] The aims of this section are to (1) perform a brief outline of the key temporal phases of the baseball pitch and

(2) link these phases to the physiological and biomechanical adaptations that occur to the shoulder in throwers/throwing athletes.

2.2.1. Biomechanical Analysis of Baseball Pitching

The baseball pitch is typically broken up into six distinct phases: wind-up, stride, arm cocking, arm acceleration, arm deceleration, and follow-through (**Figure 2.1**).[2] Events that demarcate these phases are maximum knee height (knee up), stride foot contact, maximum external rotation, ball release, maximum internal rotation, and follow-through.[10]

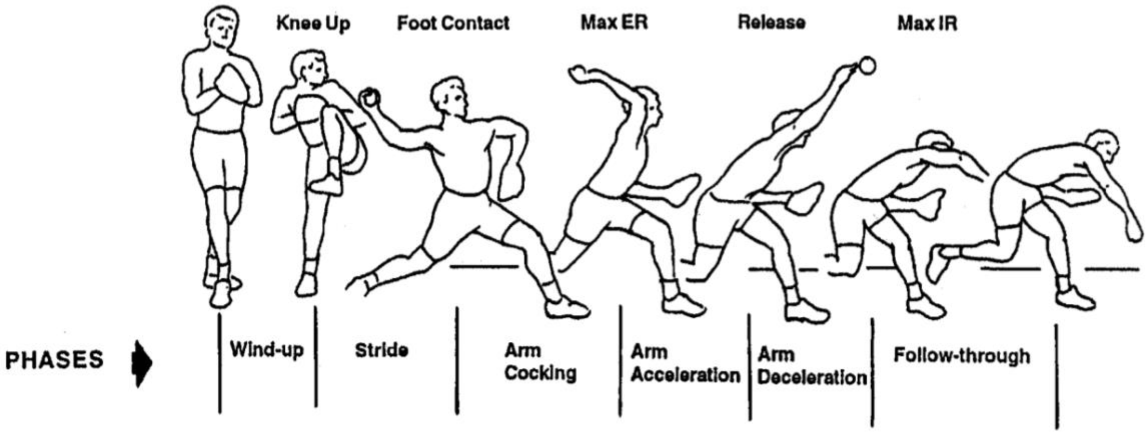

Figure 2.1 - Depiction of the phases of baseball pitching with the events that demarcate each as described by Fleisig *et al.*[2]

2.2.1.1. Wind-up and Stride Phases

The baseball pitch begins with the wind-up phase which is defined as the time between initiation of movement of the stride leg and when the knee of the stride leg reaches its maximum height.[11] As the stride leg is lifted, weight is shifted to the drive leg which begins to flex at the knee to store potential energy through the utilization of the stretch-shortening cycle (SSC). During the wind-up phase there is an insignificant amount of movement performed in the dominant arm and therefore it has little impact on shoulder adaptation. The stride phase is defined as the time between maximum knee height and stride foot contact. The importance of the stride phase is it allows the pitcher to store potential energy in the trunk, develop velocity via linear movement towards the target and set a foundation for force transfer from the lower to upper body.[12]

Biomechanical analysis of the stride phase has mostly focused on the stride length, pelvic rotation angular velocity, knee flexion angle at foot contact and arm position at foot contact.[10] The stride length of professional baseball pitchers has been measured at an average of 83.3% of their height.[13] As the stride leg moves linearly towards the target, the pelvis rotates in the same direction between 400 and 700 degrees per second and at foot contact it is approximately 27 degrees open (i.e. when looking caudally a line connecting the two hips would be 27 degrees from the X axis).[14] While the pelvis is rotation, the trunk remains relatively stationary in the transverse plane. At foot contact, it is positioned at −19 degrees when looking caudally a line connecting the two shoulders would be −19 degrees from the X axis.[1,14] The 46 degree discrepancy between the pelvis and torso enables the trunk rotators to store potential energy via the SSC which is then used to generate torque into the upper extremity.[9] Knee flexion at foot contact is associated with elbow valgus torque and shoulder external rotation torque.[12] This association is likely due to the stride leg being crucial in transferring forces from the lower body through the kinetic chain and delivering high velocities.[12]

The position of the elbow at foot contact also seems to play an important role in the amount of stress placed through the shoulder and elbow.[1] Pitchers who exhibit a greater amount of elbow flexion at foot contact seemingly show a reduction in longitudinal distraction force in the shoulder and elbow valgus stress in subsequent phases of the pitch.[15,16] At the time of foot contact, the shoulder is typically in approximately 90 degrees of abduction, 53 degrees of external rotation and 23 degrees of horizontal abduction.[2,17,18]

2.2.1.2. *Arm Cocking Phase*

The arm cocking phase is defined as the time between foot contact and maximum shoulder external rotation (MER). This phase includes the continuation and addition of pelvic and truncal rotation away from the throwing arm, respectively.[9] The pelvic and truncal rotation allows the shoulder to "lay-back" into maximum external rotation where the highest amount of varus torque is exerted through the medial elbow.[19] MER has been measured at between 165 and 175 degrees in professional pitchers, which is higher than the average passive external rotation (ER) ROM measured in a clinical setting (approximately 132 degrees).[20,21] As discussed above, the average position of the shoulder in the transverse plane at foot contact is approximately 53 degrees of external rotation, which means the shoulder rotates between 110-120 degrees in approximately 0.094 seconds.[20] The shoulder internal rotators begin contracting eccentrically during the arm cocking phase to control the amount of external rotation, resulting in the build-up of elastic potential energy for the upcoming acceleration phase.[22]

2.2.1.3. *Arm Acceleration Phase*

The arm acceleration phase is defined as the time between maximum external rotation and ball release. During this phase the trunk continues to rotate contralaterally to the throwing arm, but this can be perceived as a footnote to the amount of forceful internal rotation that is occurring at the glenohumeral joint. The shoulder moves from MER (up to 175 degrees of external rotation) to approximately 30 degrees of external rotation in approximately 0.03 s, moving at a peak angular velocity of 7,240 degrees per second.[1] The subscapularis, latissimus dorsi and pectoralis major are all contracting concentrically, with electromyography (EMG) studies often finding their activity levels are above those found in a standardized maximal voluntary isometric contraction (MVIC) test.[22,23] The elbow joint initially flexes to around 120 degrees and then rapidly extends to between 20 and 25 degrees at elbow flexion at ball release.[17,24] Maximum elbow extension velocity has been recorded at 2,320 degrees per second as EMG activity in the triceps brachii reaches values near its peak MVIC levels.[1,22] Wrist flexors also show high levels of activity as they resist the varus torque placed on the elbow in support of the ulnar collateral ligament (UCL) and flex the wrist from 25 degrees of extension to neutral at ball release.[17]

2.2.1.4. Arm Deceleration Phase

The arm deceleration phase is defined as the time between ball release and maximum internal rotation. The shoulder continues to internally rotate until it reaches zero degrees of rotation and horizontally adducts to 35 degrees while the elbow continues to extend to approximately 20 degrees of elbow flexion.[17] The external rotators contract eccentrically to decelerate the arm and oppose the distraction forces during acceleration.[1,22] Distraction forces placed on the shoulder peak at >1000 N and horizontal abduction torque peaks at >100 N·m.[2] Previous research suggests that the most important phase related to shoulder and elbow injuries is the deceleration phase due to the eccentric load on the external rotators.[25]

2.2.2. Shoulder Adaptations to Pitching

For the past 60 years, researchers have noted that the throwing shoulder and elbow of a pitcher exhibits physiological and anatomical difference to their non-dominant side.[26] Researchers have debated whether these changes are functional adaptations that are necessary to be an elite pitcher, or if they are pathological or indicative of increased injury risk. Adaptations that take place in the shoulder can be split into three categories: changes in ROM, rotational strength and alteration of the resting scapula position.[27] These changes can be observed after an acute bout of pitching and over the course of a pitcher's career by comparing to their non-dominant arm or population norms. This section aims to summarise the ROM adaptations of the shoulder with reference to the biomechanical analysis presented previously.

2.2.2.1. *Shoulder Range of Motion Adaptations*

Shoulder rotational adaptations were first reported in overhead athletes over 50 years ago, when researchers reported a decrease in shoulder internal rotation (IR) ROM combined with an increase in shoulder external rotation (ER) ROM.[28,29] These observations were made by comparing an overhead athletes dominant and non-dominant shoulders. In the years since then, this observation has been very well replicated and several explanations for this occurrence will be explored. Initially, researchers and clinicians speculated that the soft tissues of the shoulder were driving the changes in rotational ROM. The posterior capsule was investigated and fibrotic transformations in the observed.[30] Researchers concluded that these transformations were causing a decrease in elasticity of the posterior tissues during passive IR ROM testing, while repetitive stretching of the anterior capsule during MER resulted in increased ER ROM.[30]

After an acute bout of pitching, there is a high level of confidence that a pitcher exhibits greater external rotation ROM and a loss of internal rotation ROM when compared to their non-dominant arm and compared to a pre-pitching bout.[31–34] These changes to ROM have been shown to take up to 3-4 days to return to baseline.[31,34] Seeing that these changes are acute to the observable rotational ROM, they are typically attributed to an increase in the extensibility of soft tissue within the anterior structures concomitant with a decrease in posterior structure length.[30]

While acute changes in shoulder rotational ROM are well established, there is seemingly more conflicting research in assessing chronic changes to rotational ROM across an entire season. One research group examined rotational ROM in Major League pitchers' dominant and non-dominant arms immediately prior to and following a full season of pitching.[33] The authors found no difference in IR, ER and total rotational (TR) ROM, which represents the total rotational arc a shoulder can move through (i.e. IR ROM + ER ROM), across a full season. However, during a subgroup analysis separating starting pitchers and relievers, starting pitchers showed a statistically significant increase in IR and TR ROM, while relievers showed a statistically significant decrease in IR ROM.

Chronic adaptations to rotational ROM are difficult to assess and are often confounded by when the researcher measures the pitcher in relation to their most recent bout of pitching. However, in cross-sectional studies of professional baseball pitchers, an adaptation is seen towards an increase in ER with an accompanying, and equivalent decrease in internal rotation when compared to the non-dominant arm, with total rotational ROM preserved. These changes result

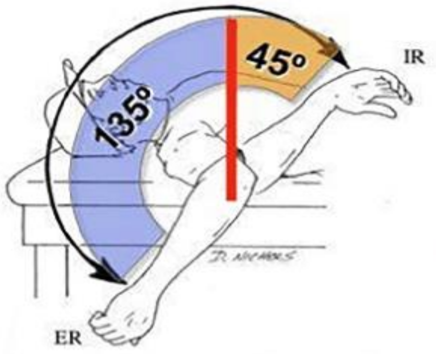

Figure 2.2 – Adapted from Nakaji *et al.* (2021). Functional adaptation of the pitcher's throwing shoulder as a result of chronic, repetitive pitching. The figure shows an increase in ER ROM and decrease in IR ROM, with TR ROM preserved.

in a pitcher's rotational arc being oriented posteriorly (**Figure 2.2**) What is less clear is whether it is soft tissue, bone, or a combination of both driving these rotational ROM changes.

Humeral torsion (HT) is a mechanism that explains bony adaptation to repeated overhead throwing. HT is defined as twisting of the humerus about its longitudinal axis.[35] Relative twisting of a bone when compared with another bone is bidirectional, and in the case of HT posterior twisting is termed retrotorsion and anterior twisting is antetorsion.[36] Beginning in utero, a newborn displays a marked amount of humeral retrotorsion which, as they become more skeletally mature, gradually becomes less retrotorted[37]. As such, a person who has more humeral retrotorsion will likely exhibit more external rotation when measured by a goniometer, while a person who has more humeral antetorsion will likely exhibit more internal rotation. HT is a phenomenon that varies greatly within and between individuals and is largely related to the persons age and throwing activity.[38,39]

Bony adaptations in the upper extremity due to external forces are more likely to occur if they are exerted before reaching skeletal maturity. It therefore follows that males who throw frequently before the age of 16, after the peak velocity of bone growth in the upper extremity is complete, are more likely to exhibit these changes in their bony structures[40,41]. A professional baseball pitcher logs a throwing activity likely in the millions of repetitions by the time they are contracted to a professional organisation, many of these occurring during their developmental years. The repetition during developmental years allows for the adaptation of bony structures to take place in the humerus such that they fight against the natural lessening of humeral retrotorsion that is taking place in their non-dominant arms. Thus, as is to be expected given these mechanisms, professional baseball pitchers show greater humeral retrotorsion in their dominant arms when compared to their non-dominant and display much greater retrotorsion when compared to non-throwers.[42]

Changes associated with increased humeral retrotorsion are only able to be measured with the use of a diagnostic ultrasound, X-ray or CT scan.[36,42,43] As such, it is far more challenging to assess humeral torsion than it is to measure an athlete's rotational ROM with a goniometer due to costs and availability. However, solely assessing rotational ROM without assessing humeral torsion means the clinician is unable to determine how much of their rotational ROM is contributed to by soft versus bony tissue adaptation.[27] For example, if a pitcher is found to have reduced internal rotation ROM but also has excessive humeral retrotorsion such that this reduction in IR can be attributed to their bony adaptation, then the mechanisms discussed earlier (such as posterior capsule changes) may not apply to this individual.

A recent study investigated whether there was a correlation between rotational ROM and humeral torsion-adjusted ROM.[44] They found humeral torsion-adjusted ROM was significantly different to the regular clinical measure of rotational ROM. The difference between torsion-adjusted ROM and rotational ROM means that measuring a pitcher's rotational range of motion is not an accurate depiction of what is driving their motion (or lack thereof) unless the clinician or researcher considers the bony changes that may affect the measurement.

Researchers have looked into the development of predictive models that can calculate an athletes humeral torsion based off other anthropometric data, age and their continent of birth have also been investigated.[45,46] Using algorithmic models to predict HT brings us a step closer to being able to predict a players torsion without having to perform the measurement, saving the cost of expensive point-of-care ultrasound equipment in clinics across the world. This method shows great promise and would likely show greater accuracy with larger datasets to analyse along with increased sophistication of machine learning techniques used.

2.3. The Burden of Shoulder and Elbow Injuries in Professional Baseball

2.3.1. Epidemiology of Shoulder and Elbow Injuries

The Major League Baseball (MLB) and Minor League Baseball (MiLB) injured list (IL) contains injury data on active players who have sustained an injury. One of the first epidemiological studies that used the IL was conducted in 2001 where a decade’s worth of injuries from 1989 and 1998 were analysed.[47] Their study showed that shoulder and elbow injuries were the highest recorded cause for a player to be assigned to the IL and were responsible for around half of all injuries (49.8%).[47]. The knee was second at 7.3%, followed by wrist/hand and back. A follow-up study replicated this finding using IL data across the 2002 through 2008 seasons and found that injuries to the shoulder and elbow accounted for 51.2% of all IL assignments.[48]

When expanded more broadly with more recent data, shoulder and elbow injuries made up 40.2% of the total injuries in MLB between 1998 and 2015.[4] While the rate of shoulder injuries and total days spent on the IL reduced over this timeframe, elbow injuries increased in both total number of injuries and days missed due to injury (5,263 in 1998 versus 10,000 in 2015). In a more recent study, the researchers used the IL to identify upper limb injury incidence over the 2010 through 2016 seasons.[49] Their results replicated previous work in finding that upper limb injuries accounted for 49% of all injuries in pitchers and position players.[49] The shoulder was found to have the highest incidence rate at 1.89 per 1000 athlete exposures (AE) followed by the elbow at 0.58 per 1000 AE and when pitchers were analysed as a subset, the incidence rate of upper limb injuries rose to 2.78 per 1000 AE.[49]

More recently, the COVID-19 pandemic impacted the 2020 season resulting in an interrupted preseason and a shortened but more condensed regular season. One study compared injury rates in the two seasons prior to the pandemic versus the 2020 season to establish whether this change in season structure impacted injury rates.[50] The incidence of upper extremity injuries in pitchers in the 2018 and 2019 seasons was shown to be 3.31 per 1000 AE and rose to 5.68 per 1000 AE in 2020. In a follow-up study in 2022, they analysed the 2021 IL data to see whether the injury rate had returned to pre-pandemic levels.[51] They found that overall, injuries in 2021 had remained the same as 2020 (8.66/1000 AE vs 8.69/1000 AE), with upper extremity injuries to pitchers lowered to 4.21/1000 AE but remaining higher than the pre-pandemic levels of 3.31/1000 AE.[51] Another study performed a Poisson regression to compare the injury rates between the 2015 through 2019 seasons versus the 2020 season.[52] For all players, the researchers found a higher incidence of elbow injuries that occurred in the 2020 season compared to the prior five seasons (2.2, $95\%_{CI}$ 1.8, 4.0, $P<0.001$).[52] When a subgroup analysis was performed on the pitchers, this increase was only found in the pitchers (3.5, $95\%_{CI}$ 2.1, 6.0, *P*<0.001), meaning there was a 3.5 times greater risk of a pitcher suffering from an elbow injury in the 2020 season compared with the five seasons preceding it.[52]

Shoulder and elbow also result in the longest time spent away from pitching.[53] Between 1998 and 2015, the shoulder and elbow accounted for 54.4% of days missed due to injury.[4] Elbow injuries drive the high number of days missed, with an injury to the ulnar collateral ligament (UCL) of the elbow taking an average of 17.1 months to return to pitching following the injury.[4]

The financial impact of injuries in MLB is substantial, with approximately $695M being spent on paying injured players along with their replacements in 2015 alone. In total across the 18 seasons, $6.7B was paid to players who were designated to the disabled list on top of $886M paid to players who replaced them at an average of $423M annually.[4]

2.3.2. Types and Severity of Shoulder Injuries

2.3.2.1. Glenoid Labrum Injuries

The glenoid labrum consists of fibrocartilaginous tissue that extends circumferentially around the glenoid fossa of the scapula.[54] The long head of biceps tendon arises from the supraglenoid tubercle, and one third of its fibres are contributed by the glenoid labrum.[54] Injuries to the glenoid labrum typically occur at this junction and are often referred to as SLAP (superior labrum anterior posterior) lesions.[55]

An initial theory on the mechanism of SLAP lesions was proposed in 1985.[56] Their theory implicated the follow-through phase of pitching where the biceps is required to contract eccentrically to control elbow extension while providing a compressive force at the shoulder to limit shoulder distraction. A cadaveric study has since shown that a higher amount of strain is placed on the biceps long head during the position the shoulder is in at MER when compared with any other throwing position.[57]More recently, consensus has since been found in an alternative hypothesis that aligns with cadaveric studies showing higher biceps tendon strain in MER. The so-called "peel-back" mechanism proposes that during the late-cocking phase, the combination of 90 degrees of abduction with MER along with the biceps tendon being confined to the bicipital groove of the humerus causes it to peel the labrum from the glenoid posteriorly.[58] This position places a large amount of torque (67 N m) on the biceps tendon and ultimately the superior labrum.[57]

There is still the question of whether these tears are pathological or not, given that a recent MRI study conducted on 21 asymptomatic professional baseball pitchers found that ten participants exhibited what the authors considered pathological SLAP lesions.[59] As discussed earlier in the adaptations section (**Section 2.2**), gaining as much external rotation ROM in the shoulder is advantageous for a baseball pitcher to achieve high velocities. Therefore, a SLAP lesion could be viewed as an advantageous adaptation to allow for greater external rotation caused by the reduction in strain being placed through the long-head of biceps as it is confined to the externally rotating bicipital groove. Perhaps this is the point where a distinction needs to be made between (1) a chronic SLAP lesions that have developed over the athlete's career of pitching allowing for continual adaptation of the surrounding tissues and (2) a traumatic SLAP lesions that is a result of a single incident that resulted in immediate onset of symptoms.

Management of symptomatic SLAP lesions in pitchers has been difficult, and only small progress has been made with the advancement of surgical and conservative treatments.[58] One study found that just 40% of those treated conservatively were able to return to playing at any level, whilst less than 1-in-4 were able to return to their previous level of performance.[60] The same study found that those who underwent surgery did not perform much better, with 48% able to return to any level and just 7% were able to return to their previous level of performance. A systematic review found that when overhead athletes are pooled together 63% of patients report returning to playing at 2-year follow-up.[61] This finding is similar to another study which found that 59% of pitchers were able to return to play following surgical intervention.[62] As such, a conservative approach is typically used as first line treatment with surgery only being performed if the athlete fails to return to pitching without pain in a period of at least 6 months.[58,60]

2.3.2.2. Rotator Cuff Tears

The rotator cuff consists of four muscles and their tendons – supraspinatus, infraspinatus, teres minor and subscapularis – all which originate from the scapula and insert into the humeral head. All four muscles exhibit high levels of activity during pitching and their roles in pitching are to provide stability to the glenohumeral joint by resisting distraction, along with accelerating and decelerating the arm to perform the pitch.[22] As such, they are placed under and produce extreme loads during pitching which leaves them vulnerable to injury.

Injury is most often caused by repetitive trauma but can also be due to acute overload of the tendon.[63] When viewed on magnetic resonance imaging (MRI) or arthroscopically, usually only partial-thickness tears are observed which has led them to be described as adaptive tears insofar as they allow the athlete to gain greater amounts of external rotation.[63,64] However, in symptomatic pitchers who require surgical management, the mean return to play is approximately 17 months, with those who do return typically experiencing a decrease in performance.[65]

2.3.2.3. Internal Impingement

Internal impingement of the shoulder is characterized by pain in the posterior shoulder when it is placed in an abducted and externally rotated position.[66] Changes to the shoulder that are associated with internal impingement include posterosuperior labral tearing, articular surface tears of the supraspinatus and infraspinatus tendons, in addition to cystic changes of the posterior aspect of the humeral head.[67] Pain due to internal impingement is purported to be caused by the articular surface of the posterior rotator cuff becoming entrapped between the greater tuberosity of the humerus and the glenoid labrum as the arm is abducted and maximally externally rotated during the cocking phase of pitching.[26,66]

Since it was first described by Bennett over 70 years ago, the pathogenesis of internal impingement has been a broadly debated topic among clinicians and researchers.[66,68] Initially thought to be caused by anterior instability of the shoulder joint, recent studies have refuted this view due to the lack of correlation between anterior translation of the humeral head and those who are symptomatic, along with studies showing the humeral head in throwers shoulders exhibit significantly more posterior translation than anterior.[69,70] Pathophysiology is currently thought to be multifactorial, with posterior rotator cuff and capsular contracture along with scapular dyskinesis being the key risk markers associated with symptomatic internal impingement.[26,66]Comparing results of surgery in this cohort is also complicated by the wide spectrum of surgical procedures that can be performed to remedy the associated pathological changes in the shoulder.[66] However, many studies show less than desired long-term outcomes in professional baseball players.[71–74]

2.3.2.4. Anterior Capsule Injury

The anterior capsule of the glenohumeral joint is a non-contractile tissue that passively inhibits anterior translation of the humeral head when the shoulder is abducted and externally rotated.[75] Injuries to the anterior band of the inferior glenohumeral ligament, which forms part of the anterior capsule, are less common than the previously discussed injuries.[63] They are associated to the age of the thrower, with repetitive external rotation in the context of an anterior capsule with decreased elasticity causes the tissue to fail.[76]Due to the smaller number of these injuries occurring, there is very little evidence directing the timeframe and success of their return to pitching. In the low powered cohort studies that have been published, surgical repair of the capsule seems to be the preferred method of treatment in these athletes with 4 out of 5 cases returning to their previous level of play by a mean of 13.3 months after surgery.[76]

2.3.3. Types and Severity of Elbow Injuries

2.3.3.1. Ulnar Collateral Ligament Sprain/Tear

The ulnar collateral ligament (UCL) is a non-contractile connective tissue located on the medial aspect of the elbow. It attaches the medial epicondyle of the humerus to the coronoid process of the ulnar and passively resists elbow valgus stress, particularly when the elbow is flexed between 30 and 100 degrees.[77,78] The amount of valgus stress placed on the elbow during the arm cocking and acceleration phases of pitching exceeds the ultimate tensile strength of the UCL.[79] As such, significant amounts of force are required to assist the UCL in stabilizing the joint through muscle contraction of the forearm flexor group.[80] If this mechanism of dynamic stability were to fail, the pitcher is likely to suffer a strain or tearing of the UCL fibres.

The UCL tear accounts for the most time spent on the disabled list out of all injuries in professional baseball, with an average of 17 months between time of injury and returning to their previous level of play.[4,53] The prevalence of those who have underwent a surgical repair of the UCL was found to be 20% of all pitchers in all of professional baseball in 2018.[81] These two factors combine to make a UCL tear a devastating injury regarding a player's development and overall success as a professional baseball pitcher.

Return to play rates after UCL reconstruction are considerably higher when compared with shoulder surgeries. In a study of 743 athletes it was found that 83% were able to return to their previous level of competition and another found that there were no biomechanical differences between those who have had UCL reconstruction and those who have not.[82,83] Similarly, a recent systematic review found return to pitching rates were 80% to 97% in 27 included studies, while return to prior level was lower at 67%-87%.[84]

2.3.3.2. Flexor-Pronator Injury

The flexor-pronator muscles are the primary muscles responsible for the elbow flexion, pronation, and supination movements. This group of muscles is composed of the medial and lateral heads of the flexor carpi ulnaris, the pronator teres, the flexor digitorum superficialis, and the flexor digitorum profundus. Due to their position relative to the UCL, they provide dynamic stability of the elbow joint against the valgus stress placed on the elbow during pitching.[85] Injury to the flexor-pronator mass occurs when this structure reaches its tensile threshold, typically during MER or the acceleration phase of pitching.[22]Injuries to the flexor-pronator mass occur in pitchers 4-times that of position players and accounts for an average of 100 days missed due to injury.[85] Injury to the flexor-pronator mass also seems to be predictive of subsequent injury, with significantly higher rates of shoulder, elbow and forearm injuries recorded in the 365 days following the initial injury.[85] Additionally, 19.4% of MLB players who sustained a flexor-pronator strain went on to undergo a UCL reconstruction in the next year.[85]

2.3.3.3. Ulnar Neuropathy (Neuritis)

Ulnar neuropathy, also known as cubital tunnel syndrome or ulnar nerve entrapment, is a condition caused by compression of the ulnar nerve at the elbow. It can be divided into three categories: compression from osteophytes or hypertrophies flexor-pronator mass, friction due to subluxation of the ulnar nerve and traction due to increased strain on the nerve from the valgus stress of pitching.[86]Common symptoms of ulnar neuropathy include pain in the forearm and hand region, numbness in the fourth and fifth fingers, tingling sensations in these areas and decreased grip strength. If left untreated it can result in permanent damage to motor nerves within that area.[87]

Surgery may be indicated if conservative treatment fails to improve symptoms in a minimum of 3-6 months.[87,88] Surgery should be used as a final recourse in baseball pitchers, given that it can lead to ongoing weakness in the flexor-pronator muscle groups and sensory changes in the hand and fourth and fifth fingers that are heavily relied on during pitching and could, therefore, be career ending.

2.4. Current Evidence of Shoulder Range of Motion as a Risk Marker for Injury in Professional Baseball Pitchers

For decades, preseason ROM screening has been conducted in professional baseball to identify those with abnormal values and reduce their risk of injury. As discussed previously, what constitutes an abnormal value, especially with regard to shoulder IR and ER, has been a hotly debated topic amongst clinicians and researchers. Range of motion is typically expressed as an absolute figure (i.e. 50° IR on the dominant arm) or a relative figure (eg. 7° deficit of IR on the dominant side versus the non-dominant side). The purpose of this section is to highlight the conflict between normal adaptation and pathologic adaptation (maladaptation) while highlighting the role of humeral torsion as a confounder to absolute and relative IR and ER ROM measurements.

2.4.1. Shoulder Internal Rotation ROM and Glenohumeral Internal Rotation Deficit

Studies consistently show that glenohumeral IR ROM decreases in a pitcher's dominant arm when compared to their non-dominant arm. In a recent systematic review, the authors found that an absolute shoulder IR of less than 44° was associated with upper extremity injuries.[89] However, in baseball research, a more comprehensively researched variable in risk marker identification is the change in IR relative to the non-dominant arm. The difference in internal rotation ROM between the non-dominant (NDOM) and dominant (DOM) arms has been given the name glenohumeral internal rotation deficit (GIRD) (GIRD = NDOM IR – DOM IR).[42,96-97] A positive amount of GIRD means a player has a greater amount of IR ROM on their non-dominant arm, or more accurately a greater loss of IR ROM in the dominant arm, likely due to the adaptations described in an earlier section (**See Section 2.2.2.**). Since it was first implicated as an injury risk marker in 1991, research has continued to replicate it as being implicated as a risk marker for shoulder and elbow injuries in baseball.[31] Greater GIRD can be a result of increased fibrotic changes in the posterior capsule causing internal impingement at the shoulder and increased valgus forces at elbow. GIRD has been associated with increased risk of suffering shoulder internal impingement, UCL insufficiency, UCL tears and elbow injuries more broadly.[90–93]

While these studies were done with scientific rigor and the hypotheses given to explain their results makes logical sense, there is a concerning feature underpinning that vast majority of risk marker identification studies in baseball pitchers. As discussed previously (see **Section 2.2.2.1.**), an athletes IR ROM is significantly altered by their bony configuration due to humeral retrotorsion. Additionally, we know from empirical evidence that pitchers who display greater amounts of humeral retrotorsion also display greater amounts of humeral external rotation.[94] This finding highlights that HT is an important confounding variable that is not controlled in any study that was analysed, meaning that we don't know how much of the athlete's IR is attributed to their bony adaptation (which is non-modifiable) or soft tissue adaptation in these injury risk studies.[95]

Another concern with GIRD is the lack of consistency in its definition and application. In a recent review, the authors collated the differing definitions of pathological GIRD having been reported in the literature as: 25°, 20°, 18°, 10% loss of IR ROM, IR ROM loss that exceeds ER ROM gain and IR ROM loss with a loss of TRROM.[29] These cut points for splitting the group into 2 were either selected by researchers or garnered from previous research where those researchers selected a cut point. Not only does this make comparing results across studies more challenging, but it also leaves clinicians interpreting the research in a state of confusion. The splitting of a continuous variable to form two groups (i.e., dichotomisation) reduces the generalisability of the studies and are not biologically plausible due to the fact that optimal cut-points will differ between cohorts.[96]

Lastly, goniometers are the most common tool used in measuring rotational ROM of the shoulder. The 95% limits of agreement (LOA) is a type of analysis that estimates the error that 95% of repeated measures would be expected to fall.[97] The 95% LOA of measuring shoulder external and internal rotation has been shown to range between 5° and 9°. This range given for LOA means that we are often making conclusions based on ranges of motion that fall into the standard error associated with the tool we are using.

2.4.2. Shoulder External Rotation ROM and Glenohumeral External Rotation Deficit

Glenohumeral external rotation deficit (GERD) uses the same definition and principle that was applied to GIRD except that it is in ER, rather than IR.[92] Although the same arguments can be made about GERD (i.e., that a ROC curve has never been used to determine the appropriate cut point) and that it is confounded by an athlete's humeral torsion, it makes more intuitive and clinical sense that it could be an injury risk marker. As discussed, it has been well established that pitchers gain ER ROM after an acute bout of pitching, as well as over the course of their career.[32-34] A reduction in ER ROM measured passively by a clinician could ultimately lead to a pitcher attempting to achieve their "normal" range during the cocking phase of pitching, resulting in tissue injury because of the restriction.

A recent study investigated preseason ER ROM measures in professional pitchers and tracked shoulder injuries in the upcoming season.[98] While they did not publish the risk of absolute ER as a risk marker for injury, they did find that those who displayed ER insufficiency (defined as

<5º of ER gain compared to their NDOM arm) had a 2.2-fold increase in likelihood of suffering a shoulder injury and 4-fold increase in likelihood of having shoulder surgery. In a separate publication using the same dataset, the authors investigated whether there was any association between preseason measures and elbow injuries and found no association between ER ROM and elbow injury.[99] Another group investigated the risk of elbow injury using a similar approach by looking at the probability of an injury per degree of GERD.[93] They found that for each degree of GERD there was a 7% increase in suffering an elbow injury in the upcoming season. However, without accounting for HT, it is impossible to say whether the participants in this study did have a true discrepancy in ER between DOM and NDOM.

2.4.3. Total Rotational ROM and Deficit

Total rotational range of motion (TR ROM) is defined as the total arc created by the shoulder in the transverse plane (TR ROM = ER ROM + IR ROM). Additionally, TR ROM deficit is the difference between the non-dominant TRROM and dominant (TR ROM Deficit = $TRROM_{NDOM} - TRROM_{DOM}$). Several studies have investigated changes in TRROM as a risk marker for shoulder and/or elbow injuries. One study found a significant difference in means of TR ROM deficit between those who have suffered a UCL injury and healthy controls (6.67º deficit versus 0.93º gain).[92] In subgrouping for pitchers with and without a UCL diagnosis, there was a great disparity in the deficit (6.96º deficit versus 1.29º gain). Similarly, another study found that when comparing those with UCL injury to matched controls there was a significant difference in means of TR ROM deficit between the two groups (7º deficit versus 3º deficit).[100] The authors also noted that 58% of the group with a UCL injury had a TR ROM deficit >5º versus 50% in the control group. Another study investigated the risk associated with having a TR ROM deficit > 5º and found that they were 2.6 times more likely to suffer an elbow injury in the upcoming season.[99]

As discussed previously and like all measurements, there is intrinsic error that is somewhat unavoidable and can reduce our confidence in the conclusions drawn from the collected data. TRROM involves measuring two different motions and adding them together, which increases the amount of error via propagation of measurement uncertainty. Regarding TR ROM and TR ROM deficit, it becomes problematic to conclude that the risk of someone being injured is greater if they have a deficit in motion by an amount smaller than the SEM.

2.4.4. Humeral Torsion

In a recent study, investigators tried to answer the relationship between HT and injury by measuring HT and tracking 255 professional baseball pitchers for shoulder and elbow injuries across 4 years of professional pitching.[101] When shoulder and elbow injuries were pooled together, there was no differences between the injured and uninjured group. However, when shoulder and elbow injuries were separated there was a statistically significant mean difference of 4^{o} between those who suffered a shoulder injury and did not, along with a significant difference of 5^{o} between the elbow injury group and uninjured[101]. However, in a recent systematic review conducted in 2020, the authors concluded that there was no significant relationship between dominant humeral torsion and injury risk.[102] They showed that the pooled mean difference between injured and control groups was 0.17^{o} (95%$_{CI}$ -1.83, 2.18).

2.5. Novel Methods in Injury Risk Marker Identification

Like many other fields, sports medicine has experienced a wave of advancement in recent years in the form of improved technology and data analytics. In baseball, this advancement has taken place mostly on the performance front and while teams have likely made similar changes internally to their injury prediction modelling, however, these models have not yet made their way into the published literature. This section aims to highlight the progress that has been made in other sports in these areas with the aim of utilizing them in baseball injury prediction, risk identification and, ultimately, prevention.

2.5.1. Injury Risk Marker Identification

Injuries are complex and occur due to interactions between multiple factors.[103] Due to this complexity, the likelihood of a single risk marker being capable of predicting an injury to an individual is extremely low and there will always be a level of uncertainty.[104,105] Even with this level of uncertainty, clinicians and researchers continue their quest to find the silver bullet for predicting injury in their respective sports. It is worth mentioning that although workload monitoring is beyond the scope of this review, it plays an important part in injury management and performance in all team and individual sports.[104] Preseason screening seemingly plays as significant a role in the medical team's injury management plan.[106] Preseason screening seemingly plays as significant a role in the medical team's injury management plan. It can be hypothesised that if an athlete exhibits an abnormal finding in certain measures, then the abnormal finding can either be addressed or the athlete be more closely monitored for injury during the season.

As discussed in the previous section (**Section 2.4**), there have been significant associations between single risk markers (e.g., TRROMD, ER strength etc.) and injuries in professional baseball pitchers. However, the assumption that a single variable interacts with injury risk as a linear function is likely incorrect, which leads us to more complex representations of data using multivariate analyses in the form of linear regression models.[107–109] Linear regression models are able to handle multiple covariates and describe the *linear* relationship between them and an outcome variable of interest. Linear regression models have begun to find their way into other sporting areas and, until the last few years, there has seemingly been a reluctance to accept these more complex statistical methods in the published baseball literature.

2.5.2. Generalised Additive Mixed Models and Injury Prediction

The generalized additive mixed model (GAMM) is a form of multivariable regression analysis that replaces the linear functional form of the relationship between covariates and outcomes with the sum of smooth functions.[110] Briefly, the GAMM is a nonparametric regression method that uses flexible smooth functions to estimate potentially nonlinear relationships between covariates and the outcome variable of interest.[111]The GAMM has started to find application within the field of risk marker identification for injuries, along with use as a prediction model in professional sports and healthcare more broadly. For example, one study attempted to predict hamstring injuries in elite Australian footballers by using previously recognised injury risk markers as covariates in a GAMM.[105] The researchers were able to produce a model that had the ability to predict a hamstring injury with an accuracy greater than random chance. The main advantages of the GAMM over linear methods (which should be specified) is that they are able to model complex behaviour between predictors (covariates) and the outcome variable as a *nonlinear* smooth function if supported by the data. When fitting more complex, particularly *nonlinear* models to multivariate data, there is a risk of overfitting. Another advantage of the GAMM is the inherent ability of the fitting procedure to protect against overfitting by offering regularisation on the smooth functions.[112] There are currently no known GAMM analyses published on upper extremity injuries in professional baseball pitchers.

2.6. Conclusion and Justifications

Baseball pitching involves one of the most violent motions on human record. The incredible amount of force generated at the shoulder and elbow used to propel the baseball leads to a large proportion of the pitchers suffering from shoulder and elbow injuries, many of them resulting in extended periods on the sideline. The impact of these injuries creates a problem for pitchers and the clinicians charged with caring for them, because the adaptations that take place in a pitcher's shoulder likely allow this to happen. However, these adaptations also create an environment where the lines are blurred between pathology and normal adaptive changes that, in the case of humeral torsion, are difficult to assess. These blurred lines are highlighted by the differences between a pitchers' dominant shoulder and that of someone in the general population, along with the number of asymptomatic pitchers seemingly playing with what we would normally consider a shoulder or elbow pathology. These adaptations have been long debated in the baseball community and amongst baseball researchers, with ultimately mixed rates of success in reducing injuries and time spent on the disabled list. Modern computing and the broader sport science community has allowed for more sophisticated predictive modelling that has sparsely made its way into the baseball literature. The use of these modern statistical methods combined with addressing of humeral torsion as an important confounding variable in shoulder ROM analysis is a significant gap that this thesis aims to fill in the remaining chapters.

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CHAPTER 3: DEVELOPING MODELS FOR PREDICTING HUMERAL TORSION IN PROFESSIONAL BASEBALL PLAYERS USING LINEAR AND FLEXIBLE NONPARAMETRIC REGRESSION

3.1. Abstract

Injuries to the shoulder and elbow of professional baseball pitchers account for the majority of all days missed due to injury. Identifying risk modifiers for arm injuries in baseball pitchers is crucial for developing preventive measures. Humeral torsion (HT), the twisting of the humerus along its longitudinal axis, plays a significant role in the rotational range of motion (ROM) of the shoulder – a key factor in injury risk assessment. However, measuring HT remains a challenge, and there is a need for more cost-effective and accessible methods. The aim of this study was to develop and compare the performance of two predictive models in their ability to estimate humeral torsion using demographic data and shoulder range of motion (ROM) as predictor variables. We hypothesised that a flexible, nonparametric regression (i.e., a generalized additive mixed model; GAMM) will demonstrate superior predictive performance in estimating HT in professional baseball players when compared with a linear mixed effects regression model (LMER). The study included professional baseball pitchers from the Cleveland Guardians MLB organization from 2010 to 2019. Modifiable and non-modifiable predictor variables including demographic data and shoulder ROM measurements were collected during spring training prior to each season. The outcome variable of HT was measured via indirect ultrasound and inclinometer by two skilled assessors. Both the GAMM and LMER models included modifiable and non-modifiable covariates as predictors. An intercept-only (null) model was also fit to the data and was used as the baseline for model comparisons. The performance of each model was assessed using the root mean squared error (RMSE) obtained via repeated K-fold cross-validation (CV).

A total of 207 pitcher-seasons from 93 players were analyzed. Likelihood ratio tests revealed that the GAMM and LMER models both significantly improved the goodness-of-fit to data over the baseline model ($P < 0.05$). The CV RMSE for the GAMM (11.55 ± 0.67°) was modestly better than obtained via the baseline model (15.72 ± 0.83°), yet was only marginally

better than for the LMER (11.82 ± 0.69°). Given that the standard error of measure in HT for professional pitchers is 1-2°, it is clear that neither the LMER nor GAMM models evidenced a low enough CV RMSE to be practically useful in predicting an individual pitchers HT from the included set of modifiable and non-modifiable covariates. Our findings indicate that, at present, both linear and flexible nonparametric approaches to predicting HT with the predictors used in this study is not a clinically worthwhile substitute for HT measured via ultrasound in professional pitchers.

3.2. Introduction

Due to the considerable health care costs and the overall burden associated with arm injuries in professional baseball, sports medicine practitioners have been striving to develop risk assessment and predictive models that detect whether changes in clinical measures of the shoulder and elbow increase the risk of sustaining an arm injury during the following season.[1] Predictive models have become powerful tools in sports medicine, offering valuable insights into injury risk assessment and prevention strategies.[2] By analysing a multitude of clinical measures, biomechanical data, and demographic variables, predictive models can identify patterns and correlations that help forecast the likelihood of an athlete sustaining a future injury.[3] These models enable sports medicine practitioners to tailor interventions, training protocols, and rehabilitation plans to individual athletes, ultimately attempting to minimize the risk of injuries.[2]

Functional adaptations occur to soft and osseous tissue in pitchers because of the forces placed through the upper extremity during repetitive pitching.[4] Soft tissue changes directly influence the rotational range of motion (ROM), but the extent of motion is ultimately determined by the underlying osseous adaptations. One particular phenomenon observed with throwing is humeral torsion (HT), which refers to twisting of the humerus along its longitudinal axis.[4–6] HT is bidirectional and is typically described as being twisted more posteriorly (retrotorsion) or anterior (antetorsion) relative to the anatomical neutral. In normal development, the humerus transitions from excessive retrotorsion during fetal development to increased antetorsion in adulthood. However, professional baseball pitchers exhibit significantly more retrotorsion in their dominant arm compared to the non-dominant side, resulting in a total arc that is shifted further into ER thereby reducing their IR when measured via goniometer/inclinometer (**Figure 3.1**). It has been theorised that the repetitive torque produced by the internal rotators combined with the inertia of the distal segments involved in the throwing action counteracts the natural aging-related antetorsion of the humerus.[7]

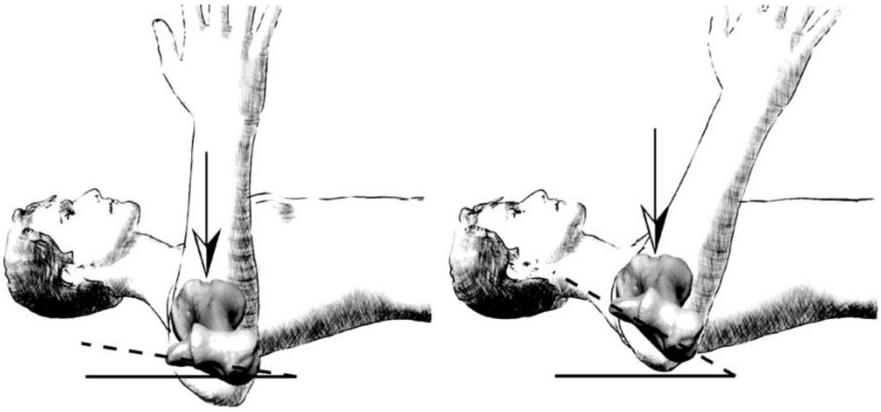

Figure 3.1. Adapted from Whiteley (2006). The illustration on the left exhibits a greater amount of humeral retrotorsion than the figure on the right. This results in an acquired change in rotational ROM to be shifted towards ER, resulting in reduced IR when measured via goniometer/inclinometer.

The variety of approaches to obtaining a HT measurement has caused confusion among researchers and clinicians.[8] Some of these methodologies include cadaver studies, X-rays, computed tomography (CT) scans, ultrasound (US) scans and magnetic resonance imaging (MRI) scans.[8] Today, CT scans are the most utilized method of obtaining HT and are recognized alongside MRI scans as the gold standard during validation studies of other methods.[9] US scans have become more popular in point-of-care settings due to their portability and significantly lower cost versus CT and MRI scans. They have been shown to be a reliable and valid measure of HT when compared to the more expensive methods with a standard error of measurement of two degrees.[9]

Despite the development of more cost-efficient methods, HT continues to remain unaccounted for in many clinical and research environments.[10] Due to its influence on an athlete's shoulder rotational ROM (illustrated in **Figure 3.1**), HT is a major confounding variable that is failing to be controlled for during risk modifier identification and performance literature. The error is compounded by the frequency in which shoulder ROM is assessed and researched without controlling for HT.[11–13] As such, there has been a recent surge in developing easier and more cost-effective ways of estimating HT, including palpation along with the development of predictive modelling to calculate an athletes HT using various other modifiable and non-modifiable variables (e.g., Shoulder IR ROM, age etc.).[6,14] Clearly there is a need for an easier and more cost-effective tool to measure HT, and the solution to this problem may reside in the development of accurate prediction models.

Therefore, the aim of this study was to develop and validate the performance of two predictive modelling approaches for the use of estimating HT in professional pitchers using only their demographic data and rotational range of motion of the dominant and non-dominant arms. The two models explored were a linear mixed effects regression (LMER), and a flexible nonparametric regression approach, i.e., a generalised additive mixed model (GAMM). The advantage of the GAMM over linear models is that it does not assume any structural form between of the relationship between predictors and outcome variables *a priori* and, instead, takes a data-driven approach to fit flexible smoothing functions to capture any potential nonlinear trends if supported by the data. We hypothesised that a GAMM would demonstrate superior predictive performance compared with a LMER model when estimating HT from only demographic and range of motion variables in professional baseball pitchers.

3.3. Methods

3.3.1. Participant Recruitment and Ethical Approval

The study included all pitchers who were contracted to the Cleveland Guardians MLB organization from 2010 up to and including 2019. The eligibility criteria were: (1) contracted pitcher with the Cleveland Guardians MLB Organization; (2) present and able to participate in a preseason evaluation for that year; and (3) did not have any complaints of shoulder or elbow pain and were not receiving treatment for a shoulder or elbow injury. This cohort study was performed with the approval of the MLB Research Committee.

3.3.2. Pitcher Demographics

Demographic data including age, height, continent of birth and throwing arm were either self-reported by the pitchers or collected by team officials. If these variables were unknown or missing, they were obtained via a publicly available website (https://www.baseball-reference.com). All these data points were found such that there was no missingness in the entire dataset.

3.3.3. Predictor Variables

Shoulder internal rotation (IR), external rotation (ER) and flexion ROM (FLEX) were assessed using an inclinometer due to its greater reliability versus a goniometer.[15] For all assessments, the inclinometer was zeroed on a 600 mm bubble level prior to assessing each participant. Two measurements of each trial were taken and the average between the two measures was used in further data analyses. Each participant had their dominant (DOM) and non-dominant (NDOM) shoulders measured. There were no actions taken to ensure the blinding of participants, assessors or researchers performing the analysis to the predictor variables of each participant.

3.3.3.1. Internal Rotation Assessment

The participants were asked to lie supine and place their shoulder into 90 degrees of abduction with their elbow at 90 degrees of flexion. The forearm was supinated and their humerus resting on the plinth with their elbow off the edge. A towel was placed underneath the humerus to ensure neutral horizontal positioning. The first assessor began by palpating the coracoid process with their thumb to stabilise the scapula. Using their other hand, they then stabilized the distal humerus by gripping over the elbow. This hand then moved the participant into shoulder IR until there was movement felt at the coracoid process – that is, there is compensatory movement of the scapular into anterior tilt. A second assessor then placed the zeroed inclinometer over the distal forearm with the end of the inclinometer resting over the radial styloid process where at this point a reading was taken and recorded.

3.3.3.2. External Rotation Assessment

The same initial position that was used for IR was then used for ER. Once the participant was relocated back to neutral, the first assessor began by placing one hand firmly over the anterior shoulder girdle to stabilise the humeral head. The assessor's other hand then grasped the participants elbow and moved the participant into shoulder ER. A second assessor then placed the zeroed inclinometer over the distal forearm with the end of the inclinometer resting over the ulnar styloid process where at this point a reading was taken and recorded.

3.3.3.3. Shoulder Total Rotational ROM

Shoulder total rotational ROM was then calculated by adding the participants IR ROM and ER ROM together: i.e., Shoulder Total Rotation ROM (TR) = IR + ER ROM.

3.3.3.4. Shoulder Flexion Assessment

The assessment began with the participant lying supine, with their hips and knees flexed. To prevent excessive scapular rising and posterior tipping, the assessor lightly stabilizes the lateral border of the scapula with their hand and moves the participant's arm through flexion in the scapular plane. The inclinometer was placed on the distal triceps and a reading was taken and recorded. If the participant's flexion is 180° or less, the exact glenohumeral joint flexion is recorded. However, if the motion exceeds 180°, the measurement is recorded as 180° since the participant's arm strikes the table on which they are lying.

3.3.4. Outcome Variable

3.3.4.1. Humeral Torsion

Humeral torsion was evaluated using indirect ultrasonographic techniques validated in a previous study[6,9]. Each assessment required two assessors – one to perform the ultrasound examination and another to place an inclinometer on the participant and record the findings. With the participant in supine with their shoulder abducted to 90º and elbow flexed to 90º, the transducer was positioned perpendicular to the long axis of the humerus on the participant's anterior shoulder. The perpendicular angle was verified using a bubble level attached to the transducer. It was aligned perpendicular to the long axis of the humerus in the frontal plane. The humerus was rotated in a manner that aligned the apexes of the greater and lesser tubercles where at their greatest height above the floor of the bicipital groove in addition to the bicipital groove appeared parallel to the horizontal plane. An inclinometer was then positioned on the ulnar side of the forearm with one end placed on the distal ulna styloid process to measure the angle of forearm in degrees inclination relative to the horizontal plane, representing the epicondylar axis and humeral torsion. If a participant returned for subsequent seasons, their humeral torsion measures were carried forward with them due to the cessation of osseous changes in the age range they were assessed. There were no actions taken to ensure the blinding of participants, assessors or researchers performing the analysis to the amount of HT of each participant.

3.3.5. Statistical Analysis

All analyses were performed in R Studio, version 2023.03.1+446 (R Core Team, R Foundation for Statistical Computing). Each player was de-identified by assigning a unique identification number and irrelevant variables in the dataset were filtered out for the data analysis phase. Missing data were investigated prior to analysis and determined to be 0%. The development of the models followed the transparent reporting of a multivariate prediction model for individual prognosis or diagnosis (TRIPOD) recommendations.[16] The TRIPOD checklist has been included in **Appendix 1**.

3.3.5.1. Null Model

An intercept-only (null) model was fit to the data wherein no covariates were included, excepting a random-intercept term for each participant. The purpose of this model was to serve as a baseline model which represented how well HT was predicted if a single value was assumed across the sampled population (i.e., the sample average HT). This null model was fit using restricted maximum likelihood method (REML) via the *lmer()* function from the *lme4 R*-package.[17]

3.3.5.2. Linear Mixed Effects Regression Model

A linear mixed effects regression (LMER) model was fit to data, whereby HT was the outcome variable, and the following variables were input as linear covariates: participant age, continent of birth, height, throwing arm, along with DOM and NDOM values of IR, ER, TR and FLEX ROM. Participant identification number (ID) was entered into the LMER as a random-intercept term to account for within participant clustering of data points. The LMER was fit using restricted maximum likelihood method (REML) via the *lmer()* function from the *lme4 R*-package.[17]

3.3.5.3. Generalized Additive Mixed Model

The GAMM estimates nonlinear trends in covariates as nonparametric functions (called "smooths") of the outcome variable (e.g., measured HT). The GAMM models were fit using the *gam()* function from the *mgcv R*-package.[18] The variables input into the GAMM were identical to that defined for the LMER, as described above in (**Section 3.3.3**) along with age, height, hand dominance and continent of birth. Predictors that were binary (e.g., continent of birth and dominance) were included in the GAMM as parametric terms, whereas all other predictors that were numerical were included as "smooth" terms. Clustering of observations within the data were accounted for by including a random-intercept term at the participant level. The GAMM was fit using the REML method. Importantly, there are several hyperparameters of the GAMM which affect its performance and thus require a principled approach to their selection. The hyperparameters relevant to this investigation were the choice of basis function type (i.e., thin-plate *vs* cubic regression *vs* penalized splines), the degree of penalization to impose on the degrees of freedom of the GAMM (i.e., the so-called ɣ value), and a binary variable indicating whether individual smooth terms could be penalised to "zero" and thus automatically "selected out" of the GAMM (i.e., the so-called "double-penalty").[19] Higher values of ɣ and the presence of a "double-penalty" both have the effect of decreasing the flexibility (or "wiggliness") of each smoothing function in an effort to minimise overfitting of the GAMM to the outcome variable. To minimise the hyperparameter search space, we set ɣ equal 1.4 as recommended by the author of the *mgcv* R-package.[18] The optimal set of hyperparameters for the GAMM was determined as that yielding the lowest RMSE obtained via repeated K-fold cross-validation (see Section 3.3.5.4. below for a detailed description of the cross-validation procedure).

3.3.5.4. Repeated K-fold Cross-Validation

The general concept of cross-validation is to split the data to fit into two partitions: the training and validation sets. In this study, we performed repeated *K*-fold cross-validation to assess the performance of a given model on unobserved data; that is, the ability of the model to generalise to new data it has not yet seen. Briefly, the procedure for repeated *K*-fold cross-validation is described by the following steps:

1. Randomly partition the full dataset into *K* separate folds.
2. Select *K*-1 folds to serve as the training set, and the remaining fold as the validation set.
3. Fit the given model on the training set.
4. Using the model fit in step 3, generate a set of predictions using the validation set.
5. Calculate relevant metric of model performance (e.g., RMSE, accuracy, precision, F1 score, etc.) using the predicted and observed values within the validation set.
6. Repeat steps 2-5 for all potential *K* folds.
7. Repeat steps 1-6 for a total *N* times.
8. Combine all performance metrics obtained from all validation sets using a measure of central tendency (e.g., mean, median, etc.) and dispersion (e.g., standard deviation, range, 95^{th} confidence percentiles, etc.)

A total of *K*N* randomly partitioned training and validation sets are thus generated, each of which a metric of model performance is obtained. In this study, we set K equal to 5 and N to 20 (e.g., 5-fold cross-validation repeated 20 times), resulting in 100 different partitions of the data into unique training and validation folds.

3.3.5.5. Comparison of Model Performance

The model performance of the null, LMER and GAMM models were assessed using a variety of methods. First, the overall goodness-of-fit of each model was examined by calculating the conditional and marginal coefficients of determination (R^2) using the entire dataset. The *conditional* R^2 represents the explanatory power of the model when predictions are made with the inclusion of random effects; whereas the *marginal* R^2 represents the explanatory power of the model using predictions where random effects are not included. A likelihood ratio test was performed to determine whether the LMER and GAMM models displayed a significant improvement in the goodness-of-fit to the full dataset relative to the null model. Statistical significance was considered if $P < 0.05$. The generalisability error for each model was inferred from the average RMSE across all validation sets obtained via repeated K-fold cross-validation.

3.4. Results

Table 3.1 reports the participant characteristics and values for the range of motion for the upper arm.

Table 3.1. Demographic and range of motion measures of participants

Demographics and Variables	Professional Pitcher Seasons (n = 207)
Individual Pitchers	93
Age (years)	22.11 (2.45)
Height (m)	1.89 (0.09)
Hand Dominance (%)	
Left	35
Right	65
Continent of Origin (%)	
North America	66
Latin America	34
Dominant Humeral Torsion (°)	-1.25 (12.64)
Dominant Internal Rotation (°)	45.90 (8.66)
Dominant External Rotation (°)	116.87 (10.40)
Dominant Total Arc (°)	162.77 (11.75)
Dominant Flexion (°)	155.81 (12.39)
Non-Dominant Humeral Torsion (°)	16.49 (13.23)
Non-Dominant Internal Rotation (°)	56.74 (9.63)
Non-Dominant External Rotation (°)	106.97 (10.22)
Non-Dominant Total Arc (°)	163.71 (11.79)
Non-Dominant Flexion (°)	158.58 (12.11)

Participant demographics, ROM and HT measures presented as mean (SD) or percentage. A negative HT represents retrotorsion, while a positive HT represents antetorsion.

Ninety-three participants were eligible for the study and combined for 207 professional baseball pitcher seasons. The average age of the participants across the span of the study was

22.1 (SD 2.45) years of age at the time of pre-season testing. The continents of birth for this cohort were Latin America (n = 70, 34%) and North America (n = 137, 66%).

The optimal hyperparameters used for the final GAMM model were thin-plate splines for the basis functions of the "smooth terms", and the presence of a "double penalty" (i.e., *select* = TRUE). The performance of the null, LMER and GAMM models are reported in **Table 3.2**. The LMER and GAMM models were both significant improvements in goodness-of-fit to the data compared with the null model ($p < 0.01$). The LMER model showed a higher R^2 than the GAMM with random effects included for predictions (i.e., conditional R^2). Conversely, the GAMM showed a marginally higher R^2 with only fixed effects used to make predictions (i.e., marginal R^2). The GAMM and LMER model showed a similar RMSE and CV mean error for the prediction of HT. A histogram plot of the residuals of each model is shown in **Figure 3.2**, while **Figure 3.3** compares the predictions of the null, LMER and GAMM models with the actual measured values on the training, validation and full datasets.

Table 3.2. Performance metrics of the null, LMER and GAMM models.

	Full Dataset				Validation Dataset		
Model	**Conditional R^2**	**Marginal R^2**	**df**	***P*-value**	**CV RMSE (SD)**	**CV Mean Error**	**$CI_{95\%}$**
Null	0.271	-	3	-	15.72 (0.83)	1.18	-27.01, 34.56
LMER	0.746	0.454	12	<0.001	11.82 (0.69)	1.51	-20.76, 23.52
GAMM	0.688	0.481	58.96	<0.001	11.55 (0.67)	0.98	-21.79, 22.14

Performance metrics for the Null, LMER and GAMM models when used for prediction of HT on the validation and full datasets. df: Degrees of Freedom; CV RMSE: Cross-validated residual mean squared error; CV Mean Error: Cross-validated mean error; $CI_{95\%}$: 95% confidence interval of the CV RMSE

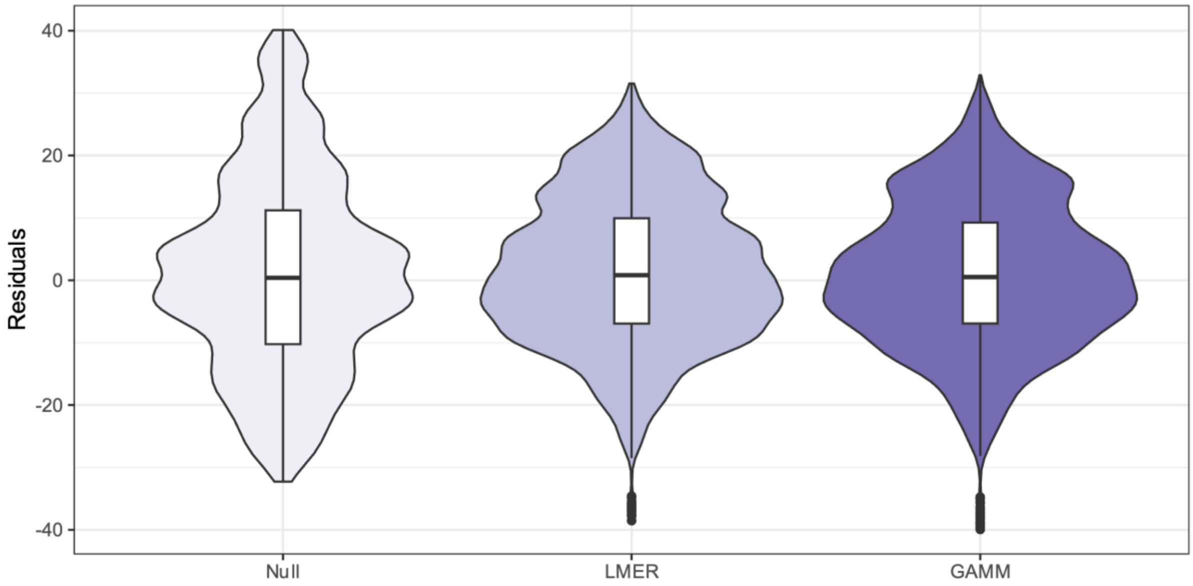

Figure 3.1.- Violin plot with box (white boxed area) and whiskers (vertical black lines) plot of residuals for Null, LMER and GAMM model predictions on the validation dataset

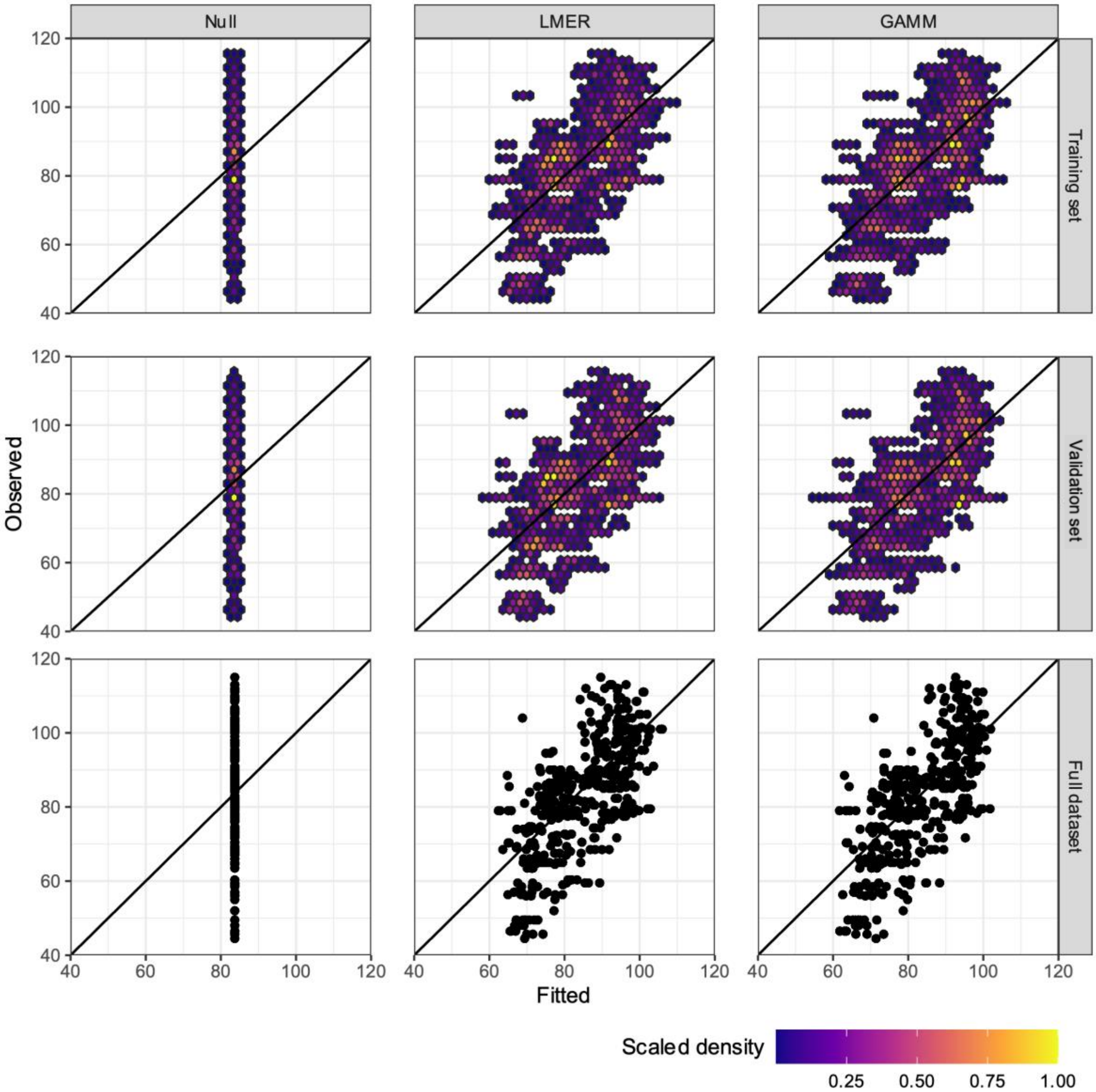

Figure 2.3. Density plots of observed versus fitted data. Plots are grouped in rows by training, validation and full datasets. Each column is grouped by the Null, LMER and GAMM models. The plots for the training and validation datasets used a coloured scale to represent the density of the outcomes.

3.5. Discussion

The aim of this study was to compare the ability of a linear regression and flexible nonparametric model to predict humeral torsion in professional baseball pitchers. Overall, the LMER and GAMM models were similar in their generalisability (i.e., predicting HT using unobserved data), showing a CV RMSE of approximately 12°. The CV RMSE of the LMER and GAMM models were considerably higher than the standard error of measurement of US measured humeral torsion in baseball players, which has been reported as 1-2°.[9,20]

An error of measurement in HT of 12° is meaningful clinically. For example, in the case of the injured player presenting for the first time to a clinician, their baseline rotational ROM is unknown and will likely be altered due to the injury when measured. Without an accurate HT measurement, it is impossible to determine the amount of rotational ROM that can be attributed to soft tissue or osseous architecture. If either of the LMER or GAMM models were used to determine the amount of HT on this injured athlete using either participant-reported or previously recorded baseline shoulder ROM measures and an error of 12° was then made on the dominant side, predicting the non-dominant HT and calculating the difference in torsion with only compound this error. If the player is deemed to have internal rotation loss without the presence of an accurate HT measure, the clinician will erroneously prescribe rehabilitation exercises to address this impairment, with associated costs involved. Subsequently, there is the potentially detrimental effect of stretching and exercising the participant into ranges of motion that are outside of their normal functional limits.[6]

It may be seen from **Figures 3.2** and **3.3** that the residual scores of the model fit are non-normally distributed. This observation hints at the possibility that the chosen model structure may have been somewhat misspecified. That is, the relationships between the various measurements of ROM and humeral torsion do not appear to be adequately predicted by the sum of their individual effects alone. Rather, it is possible that these data may have been better modelled using more complex approaches which automatically handle nonlinear interactions between covariates; e.g., random effects, gradient boosting machines, neural networks, etc. These models, however, are not directly amenable to the inclusion of random effects in their model structure and, as such, we chose to utilise a GAMM approach in the analysis.

The results of this study align with other recent publications investigating the use of linear regression and machine learning models to predict HT. One study developed a linear regression model to predict HT in professional baseball players using similar, but not identical, predictor variables in this study.[14] In addition to shoulder ER and IR ROM, age, throwing arm and continent of birth, the authors included horizontal adduction and arm history. Their model produced an RMSE of 12^{o}, which aligns with the results presented in this study. Another attempt at using computer algorithms to predict HT compared a linear regression model with various machine learning models (Random Forest, Gradient Boosting Machine, Support Vector Machine Regression and Artificial Neural Networks).[21] These authors found that the machine learning models had similar effectiveness at predicting HT compared with a linear regression model (RMSE = 9^{o} for the Random Forest and Gradient Boosting Machine versus 12^{o} in the linear regression model).[21] While the machine learning models were able to slightly reduce the prediction error, their calibration was reported as being higher than the linear regression.

Humeral torsion in the dominant arm of professional baseball pitchers has been associated with injury risk.[10,22–24] One study analysed the relationship between humeral torsion, injury and injury severity in professional baseball pitchers.[22] They showed that for every 10^{o} increase in humeral retrotorsion (i.e. a greater negative value in this study), the risk of a severe (≥30 days of missed pitching activities) shoulder or elbow injury occurring in the upcoming season decreased by 30%. The example given in the study suggests that a pitcher with 25^{o} HT has an estimated probability of injury equal to 66%, compared with a player presenting with 35^{o}

humeral torsion who has an estimated probability of injury equal to 37%. If the models developed in this study were used in a clinical setting, the error from both the LMER and GAMM would account for a 30% error in injury risk assessment, which is a clinically meaningful number.

There are several proposed reasons for this amount of error in the models, which also highlights the limitations in the inferences made from this study. The first is that the sample size in this study is significantly smaller than the previous study using similar methods to predict humeral torsion.[14] A smaller sample size has been shown to impact RMSE while simultaneously decreasing our confidence in the inferences we can make from the output due to the lack of novel data to externally validate the models' prediction accuracy.[25] In this study, a cross-validation procedure using test and validation sets to perform hyperparameter tuning was used, whereas using nested cross-validation where a training set is held out prior to hyperparameter tuning would make the lead to more confidence in the validation error shown. However, the small sample size meant that this would have diminished the training dataset even further, but shoulder be considered during future research with larger datasets. Secondly, this dataset included 93 participants who pitched in 207 seasons, with HT values carried across all played seasons as HT is unlikely to change given the age of the participants. Carrying the HT measures across seasons was done to increase the sample size to a reasonable level to make more valid inferences on the output model. However, the modifiable predictors used in the models (i.e., the shoulder ROM variables) are known to fluctuate depending on acute and sub-acute throwing load.[26] This relationship is highlighted in **Figure 3.2**, with several instances across all models where the observed value remained the same and the predicted value changed, depicting several instances of clustered horizontal rows of low-density hexagons in regions that show high residuals.

3.5.1. Conclusion

The LMER and GAMM models developed to predict HT in professional baseball players demonstrated good predictive performance. Both models were similar in their predictive performance when analysing known and novel datasets. However, the typical error of these models was much greater than the standard error of measurement of direct ultrasound assessments of HT. Therefore, these models should not be used as a substitute by clinicians and researchers if more sophisticated hardware is available to them for the assessment. Future research should aim at expanding and combining datasets to refine the models further and reduce the mean error associated with their predictions. Incorporating additional modifiable and non-modifiable predictor variables that were not presented in this study could also help to refine the models and bring exposure to which variables are seemingly more important.

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CHAPTER 4: THE INFLUENCE OF FUNCTIONAL SHOULDER RANGE OF MOTION ON SHOULDER AND ELBOW INJURIES IN PROFESSIONAL BASEBALL PITCHERS

4.1. Abstract

Data-driven analysis in professional baseball plays a crucial role in reducing the financial burden caused by player injuries. Significant resources are poured into injury risk reduction and prevention each professional baseball season. Shoulder and elbow injuries have consistently ranked as the most prevalent over the past several decades. Efforts to reduce these injuries have consisted primarily of athlete pre-season screening and monitoring, and the use of univariate analyses. This study aimed to use a generalised additive mixed model (GAMM) to assess the relationship between functional rotational range of motion (ROM) to shoulder and elbow injuries in baseball pitchers to provide insights into injury prediction and prevention. Pitchers from the Cleveland Guardians MLB organization from 2010 to 2019 were included. Preseason evaluations were conducted, including shoulder internal rotation ROM, external rotation ROM and humeral torsion assessment. Functional rotation ROM and asymmetry indices between sides were then calculated using the raw collected data. Injuries were tracked using the Health and Injury Tracking System (HITS). A GAMM was used to analyse the relationship between explanatory variables and shoulder and elbow injuries. Ninety-three subjects and 207 pitcher seasons were included in the study. Functional ROM variables showed significant differences, with dominant internal rotation (IR) being the most significant explanatory variable in its relationship to injury. The GAMM showed a U-shaped relationship between functional IR and shoulder and elbow injuries in baseball pitchers, with those exhibiting below 26^{o} and above 73^{o} deemed to be at higher risk of injury ($P < 0.05$). Future research should consider controlling for humeral torsion and explore additional explanatory variables in larger datasets with higher injury prevalence.

4.2. Introduction

In the world of professional sports, baseball stands out as an innovator that is rich in data-driven analysis, offering an array of metrics to assess and measure player performance and injury.[1–4] As was discussed in Chapter 2 (**Section 2.3**), injuries to baseball players and their placement on the disabled list costs franchises hundreds of millions of dollars and there is certainly a need for data-driven analysis to reduce this burden.[5]

The emergence of advanced algorithms and statistical computing has revolutionised the analysis of "big data" and enhances the ability to gain insight from large, historical datasets. Baseball can benefit from these advancements, particularly to improve the understanding of crucial modifiers that contribute to shoulder or elbow injuries in pitchers and inform sport medicine practice. The generalized additive mixed model (GAMM) is included as one of the solutions to this problem.[6] An overview of the GAMM, and their implementation can be viewed in **Section 3.3**. Briefly, the GAMM is a type of statistical model that can be used to describe the relationship between a dependent variable and one or more independent variables using a distributional link function.[6] However, the GAMM extends the popular generalized linear mixed model (GLMM) by allowing for more flexibility in the specification of the relationship between the outcome and explanatory variables. More importantly, the GAMM offers an interpretation of the relationship between explanatory and outcome variables with no *a priori* assumption that the relationship should be linear in form.[7] That is, the GAMM is a flexible nonparametric approach that can capture nonlinearities if supported by the data.[8]

As discussed in **Chapter 2** (**Section 2.2.2.1.**), much of the prior research has investigated shoulder range of motion (ROM) as an independent risk modifier for injury without controlling for the confounding humeral torsion (HT) in subjects. Briefly, HT is defined as the twisting of the humerus about its long axis in a posterior or anterior direction relative to the humeral head.[9]

Twisting of the bone in a posterior direction is termed humeral retrotorsion, while twisting anteriorly is termed humeral antetorsion.[10] It is well established in the literature that baseball pitchers exhibit greater dominant arm humeral retrotorsion relative to their non-dominant arm.[11] This adaptation is theorised to occur due to the repetitive and excessive forces associated with pitching and contributes to the posterior shift in total rotational arc consistently seen in baseball pitchers. That is, baseball pitchers show a significant increase in shoulder external rotation (ER) and decrease in internal rotation (IR) ROM, and HT has been suggested to contribute to this shift.[12–14] HT is a confounding variable that should be controlled for when performing any statistical analysis involving its measurement, or the measurement of ER and IR ROM in the context of assessing their impact on injury.[15] **Figure 4.1** depicts a directed acyclic graph (DAG) showing that shoulder IR ROM has a direct effect on medial elbow injury.[15] However, this effect is modified by HT. Since HT also influences shoulder IR ROM, it must be accounted for when determining the extent to which shoulder IR ROM has on medial elbow injury.[15] Unfortunately, it is a rare occurrence to find studies which have controlled for humeral torsion as a confounding variable when studying injury risk modifiers, with only one such study known to the author at the time of writing.[16]

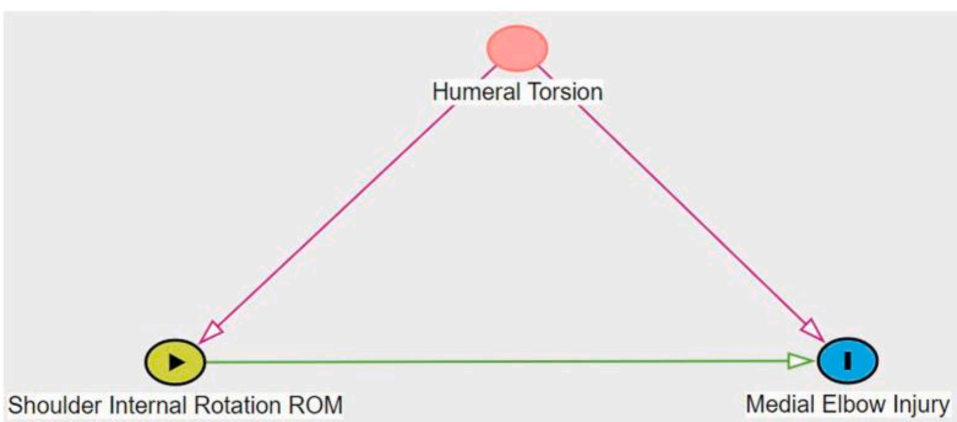

Figure 4.1 – Adapted from Bullock et al.[15] A directed acyclic graph showing the effect shoulder IR ROM has on medial elbow injury (green arrow). The red arrows show the effect that HT has on both shoulder IR ROM and medial elbow injury, thus, it must be accounted for when determining the magnitude of the effect shoulder IR ROM has on medial elbow injury.

A study in elite volleyball players used a novel method of assessing a torsion transformed ER and IR.[17] The authors of the study shifted the anatomical neutral position from a vertical position (i.e., anatomical neutral) to the position where the HT was measured (**Figure 4.2**). The transformation of neutral according to a person's HT theoretically provides a more accurate depiction of how much ROM is being utilised each direction.[17] The term we will use to describe shoulder rotational ROM when using the transformed neutral is "functional ROM".

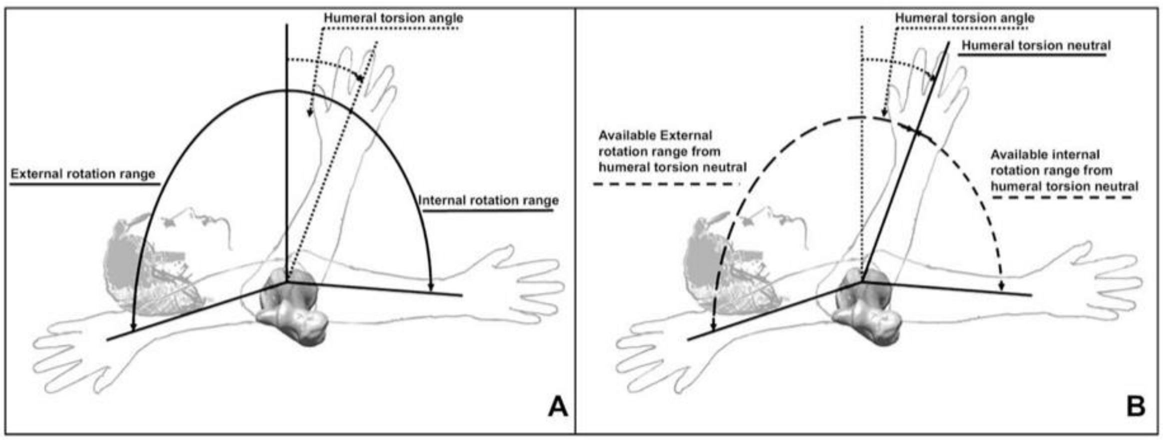

Figure 4.2 – Adapted from Schwab et al.[17] A method of obtaining the functional ER and IR ROM in participants. (A) shows the anatomical neutral as a thick black vertical line. (B) shows the HT neutral as a thick black line, with the available ROM of ER and IR from this modified neutral. The term "Functional ER/IR ROM" will be used when referring to ROM using this transformed neutral.

As it stands, most cross-sectional and cohort research attempting to identify modifiable risk modifiers for shoulder and elbow injury has focussed attention on univariate analysis. Typically, variables are measured during the preseason period, with researchers then performing injury surveillance throughout the following in-season to determine which variables were most correlated with injured athletes. While this type of analysis has given us insight into adaptations of baseball pitchers and increased our understanding of the relationships between physiological measurements (e.g. range of motion (ROM)) and injury risk, it has likely resulted in an oversimplification of an extremely complex phenomenon.[18] There main flaw in these approaches is that they strictly assume that explanatory variables exhibit a linear relationship with the outcome variable (i.e., Injury), a flaw that can be addressed with a GAMM approach.

Therefore, this study aimed to use a GAMM to assess the variable with the greatest influence on shoulder and elbow injuries in the upcoming season. The model was developed using a functional rotational ROM, estimated by altering the subject's rotational ROM from the standardised neutral position to a torsion-transformed neutral (**Figure 4.2**). The study also aimed to interpret the explanatory variables in the model in relation to their impact on injury prediction, aiding in future screening, intervention and injury surveillance. We hypothesized that the functional rotational ROM variables would show a relationship to injury risk.

4.3. Methods

4.3.1. Participant Recruitment

The study was a retrospective cohort study which included all pitchers who were contracted to the Cleveland Guardians MLB organization from 2010 up to and including 2019. The inclusion criteria were (1) contracted pitcher with the Cleveland Guardians MLB Organization, (2) present and able to participate in a preseason evaluation for that year, (3) didn't have any complaints of shoulder or elbow pain and were not receiving treatment for a shoulder or elbow injury. This cohort study was performed with the approval of the MLB Research Committee. The study followed the Strengthening and Reporting of Observation Studies in Epidemiology (STROBE) guideline which has been included in **Appendix 2**.[19]

4.3.2. Confounding Variables

4.3.2.1. Demographic Data

Demographic data including age, height and throwing arm were either self-reported, collected by team officials, or if they were still unknown it was obtained from a publicly available website (www.baseball-reference.com).

4.3.3. Explanatory Variables

All pitchers were expected to undergo pre-season evaluation which included the following range of motion measures: shoulder internal and external rotation and humeral torsion. Shoulder internal rotation (IR), external rotation (ER) and were assessed using an inclinometer. Two measurements of each trial were taken and the average between the 2 measures was used in data analysis. Each participant had their dominant (DOM) and non-dominant (NDOM) shoulders measured.

4.3.3.1. Internal Rotation Assessment

The participants were asked to lie in supine and place their shoulder into 90 degrees of abduction with their elbow at 90 degrees of flexion. The forearm was supinated and their humerus resting on the plinth with their elbow off the edge. A towel was placed underneath the humerus to ensure neutral horizontal positioning. The first assessor began by palpating the coracoid process with their thumb to stabilise the scapula. Using their other hand, they then stabilized the distal humerus by gripping over the elbow. This hand then moved the participant into shoulder internal rotation until there was movement felt at the coracoid process – that is, there is compensatory movement of the scapular into anterior tilt. A second assessor then placed the zeroed inclinometer over the distal forearm with the end of the inclinometer resting over the radial styloid process where at this point a reading was taken and recorded.

4.3.3.2. External Rotation Assessment

The same initial position that was used for IR was then used for ER. Once the subject was relocated back to neutral, the first assessor began by placing one hand firmly over the anterior shoulder girdle to stabilise the humeral head. The assessor's other hand then grasped the participants elbow and moved the participant into shoulder external rotation. A second assessor then placed the zeroed inclinometer over the distal forearm with the end of the inclinometer resting over the ulnar styloid process where at this point a reading is taken and recorded.

4.3.3.3. Humeral Torsion

Humeral torsion was evaluated using indirect ultrasonographic techniques validated in a previous study. Each assessment required two examiners – one to perform the ultrasound examination and another to place an inclinometer on the subject and record the findings. With the patient in supine with their shoulder abducted to 90^{o} and elbow flexed to 90^{o}, the transducer was positioned perpendicular to the long axis of the humerus on the participant's anterior shoulder. The perpendicular angle was verified using a bubble level attached to the transducer. It was aligned perpendicular to the long axis of the humerus in the frontal plane. The humerus was rotated in a manner that aligned the apexes of the greater and lesser tubercles where at their greatest height above the floor of the bicipital groove in addition to the bicipital groove appeared parallel to the horizontal plane. An inclinometer was then positioned on the ulnar side of the forearm with one end placed on the distal ulna styloid process to measure the angle of forearm in degrees inclination relative to the horizontal plane, representing the epicondylar axis and humeral torsion. This was then converted to degrees of inclination from the vertical plane by subtracting the value from 90. Therefore, the greater degree of humeral retrotorsion would result in a greater negative number. If a subject returned for subsequent seasons, their humeral torsion measures were carried forward with them due to the cessation of osseous changes in the age range they were assessed.[11]

4.3.3.4. Calculation of Functional Rotational Range of Motion

Internal and external rotation were then transformed using the torsion measure as the subjects neutral (i.e., Functional neutral), rather than anatomical neutral. The following equations were used to calculate functional rotational ROM: (1) Functional ER = HT + ER and (2) Functional IR = IR – HT

4.3.3.5. Calculation of Directional Asymmetry Index

Asymmetry index is used to express the side-to-side asymmetry as a percentage rather than an absolute difference. The following equation was used to calculate asymmetry index which was extracted from Killeen et al:[20]

$$dASI = \frac{Dominant - NonDominant}{\max\left(Dominant, NonDominant\right)} \times 100$$

4.3.4. Outcome Variable

4.3.4.1. Injury Tracking

Injuries were collected using the Health and Injury Tracking System (HITS) provided by Major League Baseball. This system uses the International Classification of Diseases, Tenth Revision (ICD-10) for classification of injuries and is an electronic medical record keeping system which enables the user to access de-identified medical records. Injuries are logged into the database by athletic trainers and medical personnel as they occur. All injuries and health related records in the timeframe for the study were exported to a Microsoft Excel (Version 16.74) spreadsheet. The dataset was then filtered for individuals who met the following criteria:

1. The injury occurred between 2010 through 2019 inclusive while playing for the Cleveland Guardians major and minor league teams
2. The injury occurred to the upper limb, arm, shoulder, elbow, and forearm in the dominant arm and the injury did not occur to a bone in the upper extremity
3. The injury occurred in-season (i.e., Spring Training and Winter League injuries were excluded)
4. The injury resulted in a loss of time ≥ 7 days

Once data cleaning was completed the injury and evaluations datasets were imported into R Studio (Version 2023.03.1) for joining and analysis.

4.3.5. Statistical Analysis

All analyses were performed using R Studio (Version 2023.03.1).[21] Each player was de-identified by assigning a unique identification number. The evaluation dataset was joined with the HITS injury dataset using unique player identifiable variables. Irrelevant variables in the dataset were then filtered out and evaluation data was mutated to represent dominant and non-dominant side, as the original recording of measurements was performed using right and left. Missing data were investigated prior to analysis and determined to be 0%. A paired samples t-test was performed to assess differences between raw and functional ROM measures, whereby statistical significance was achieved if $P < 0.05$.

4.3.5.1. Generalised Additive Mixed Model

The GAMM estimates nonlinear trends in covariates as parametric (linear) and nonparametric functions (called "smooths") of the outcome variable. In this study, the outcome variable was the binary indicator for upper arm (shoulder or elbow) injury occurring during the in-season period. As such, a logistic GAMM was fit to the dataset using the binomial distributional family using the *gam()* function from the *mgcv* R-package.[6] The variables included as explanatory variables in the logistic GAMM were participant age, height, nationality, and the functional ER and IR of the shoulder, and the corresponding measures of asymmetry between each limb (i.e., dASI for ER and IR, respectively). Explanatory variables that were binary in nature (e.g., nationality) were included in the GAMM as parametric (linear) terms, whereas all other explanatory variables that were numerical were included as "smooth" terms. Clustering of observations within the data were accounted for by including a random-intercept term at the participant level. The GAMM was fit using the restricted maximum likelihood (REML) method. As described in **Section 3.3.5.3.** of **Chapter 3,** the GAMM fitting procedure requires tuning of the following hyperparameters: the choice of basis function (i.e., thin-plate *vs* cubic regression *vs* penalized splines); the degree of penalization to impose on the degrees of freedom of the GAMM (i.e., ɣ value); and the flag variable indicating whether individual smooth terms could be penalised to "zero". To minimise the hyperparameter search space, we set ɣ equal 1.4 as recommended by the author of the *mgcv* R-package.[8] The optimal set of hyperparameters was obtained via repeated *K*-fold cross-validation as described in **Section 3.3.5.4..** In this study, however, the set of hyperparameters yielding the largest area under the precision-recall curve (AUPRC) were chosen as the optimal hyperparameter set.[22] The AUPRC was chosen as the criterion metric for hyperparameter tuning because this metric offers a fairer evaluation of model performance when the outcome variable (i.e., injury) is heavily unbalanced. such as occurring in our dataset (i.e., conditional prevalence of upper arm injury was 12% in our cohort).[22] Once the optimal hyperparameters were obtained, a final (optimal) GAMM was fit to the entire dataset.

The generalisability error the optimal GAMM for each model was inferred from the balanced accuracy, average precision, F1 scores and AUPRC obtained via repeated *K*-fold cross-validation. It is emphasised that in the context of the GAMM, the effect of a nonlinear smooth term on the dependent variable (i.e., probability of injury) cannot be characterised by any single number and, as such, one must investigate the nonlinear effect over the domain of the curve. Therefore, it was necessary to examine any significant ($P < 0.05$) smooth terms to determine which values of the covariate displayed probabilities of injury that were different from the baseline injury prevalence (i.e., the intercept of the model).[23] Only those values of the covariate where the 95% confidence intervals of the estimated smooth did not include a value equal to that of the intercept were considered significant at the α-level of 0.05.[23]

4.4. Results

Ninety-three participants were eligible for, and included in, the study. Participant characteristics and injury prevalence can be viewed on **Table 4.1**.

Table 4.1. Demographic and injury data of participants

Demographics	Professional Pitcher Seasons (n = 207)
Individual Pitchers	93
Age (years)	22.11 (2.45)
Height (m)	1.89 (0.09)
Hand Dominance (%)	
Left	35
Right	65
Injuries (n)	25
Injury Prevalence (%)	12

Participant demographics and injury prevalence presented as mean (SD), n, and percentage where specified.

4.4.1. Summary of Explanatory Variables

Raw and functional ER, IR and dASI measures can be viewed in **Table 4.2**. Participants had a mean raw dominant IR of 46^{o} and ER of 117^{o}. Functional mean IR and ER in the dominant side were 47^{o} and 115^{o} respectively. There was no statistically significant difference between means of the raw and functional IR and ER in the dominant arm. Non-dominant mean raw IR and ER were 57^{o} and 107^{o} respectively. The non-dominant functional IR and ER were 41^{o} and 123^{o} respectively. Raw external rotation dASI was 7% greater on the dominant side, but when transformed for torsion it was shown to be 5% greater on the non-dominant side. Raw internal rotation dASI was found to be 13% greater on the non-dominant side and when transformed for torsion it was 8% greater on the dominant side. On average, HT was measured at 1° of retrotorsion in the dominant arm and 16° of antetorsion in the non-dominant arm, with high inter-individual variability.

Table 4.2. Participant raw and functional explanatory variables

Variable	Raw ROM Mean (SD)	Functional ROM Mean (SD)	*P*-value
Dominant Internal Rotation	45.90 (8.66)	47.19 (12.88)	0.93
Dominant External Rotation	116.87	115.36 (13.38)	0.14
Non-Dominant Internal Rotation	56.74 (9.63)	40.53 (13.37)	<0.001
Non-Dominant External Rotation	106.97	123.00 (12.98)	<0.001
External Rotation dASI (%)	6.84 (7.15)	-4.96 (9.07)	<0.001
Internal Rotation dASI (%)	-12.75	7.74 (15.91)	<0.001
Dominant Humeral Torsion	-1.25 (12.64)	-	
Non-Dominant Humeral Torsion	16.49 (13.23)	-	

Participants raw and functional explanatory variables expressed as mean (SD). dASI: Dominant Asymmetry Index. A positive dASI equates to the dominant side having greater ROM than the non-dominant side. A negative humeral torsion value indicates there is greater humeral retrotorsion.

4.4.2. Generalised Additive Model

Summary data for the final GAMM can be found in **Table 4.3**. There was a significant effect of functional IR on shoulder and elbow injury risk ($P < 0.01$) (**Table 4.3**). There was no significant random effect at the participant level on shoulder and elbow injuries ($P > 0.05$). There were no significant effects of any remaining explanatory variables on shoulder and elbow injuries ($P > 0.05$).

Table 4.3. Summary of the generalised additive mixed model (GAMM).

Parametric Coefficients				
	Estimate	**Standard Error**	**Z Value**	**p-value**
(Intercept)	-2.18	0.409	-5.320	**<0.001**
Continent	0.118	0.494	0.239	0.811
Approximate Significance of Smooth Terms				
	Estimated *df*	**Reference *df***	**F Value**	**p-value**
Random Effects (ID Variable)	0.00134	91	0.001	0.479
Dominant Functional ER	<0.001	9	0	0.662
Dominant Functional IR	2.522	9	10.283	**0.003**
dASI Functional ER	<0.001	9	0	0.709
dASI Functional IR	0.694	9	2.258	0.068
Height	<0.001	9	0	0.944
Age	<0.001	9	0	0.373

Summary of the generalised additive mixed model (GAMM). ***df***: degrees of freedom; Bolded *P*-value denotes a significant influence of the covariate term on shoulder and elbow injury in the upcoming season

Figure 4.3 shows the plots of each smooth of the GAMM. The only smooth term to display a significant ($P < 0.001$) increase in the probability of shoulder or elbow injury (above the model intercept) was dominant functional IR ROM. Specifically, the probability of elbow or shoulder injury was higher than baseline prevalence when dominant functional IR ROM was either below 26^{o} or above 73^{o}.

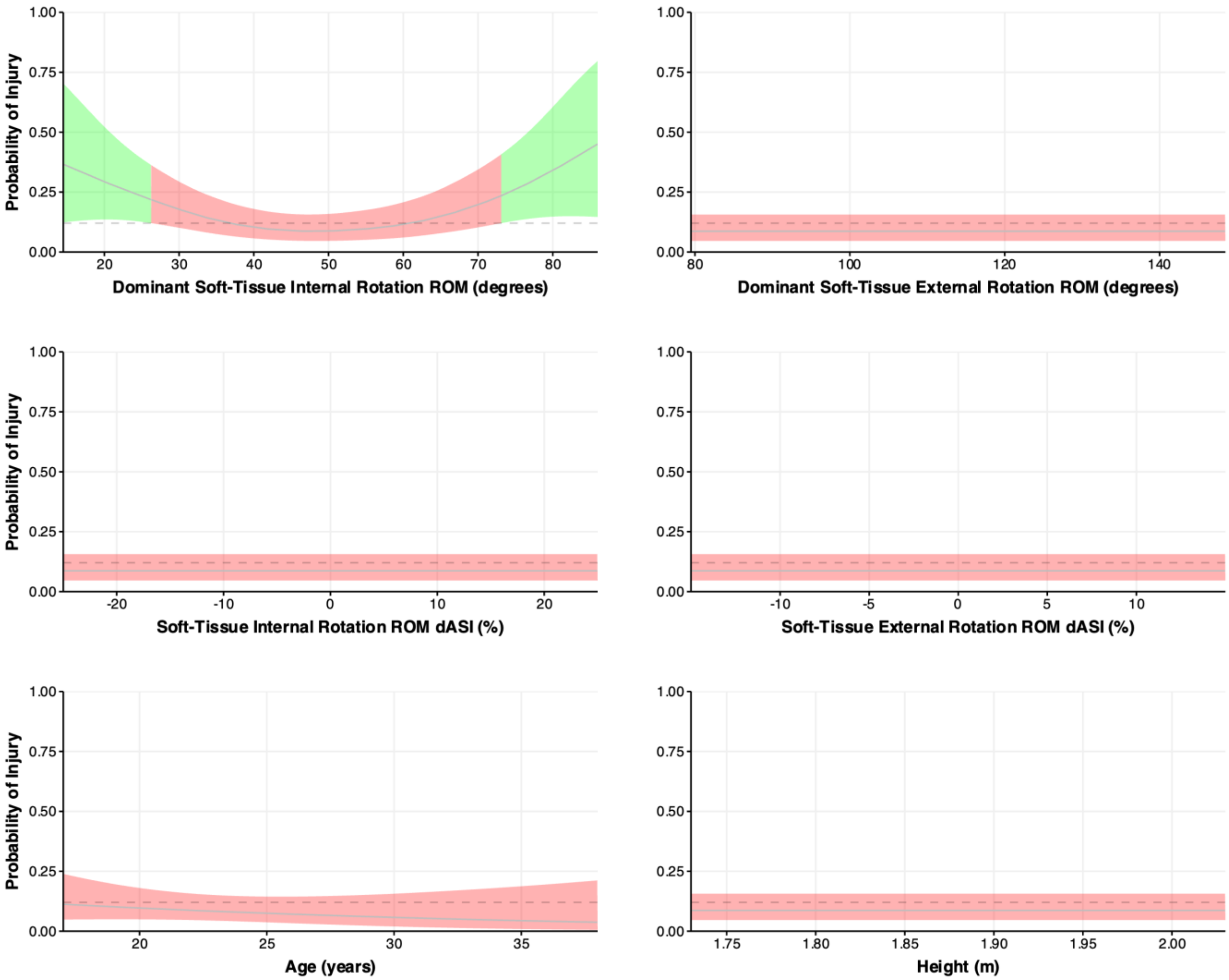

Figure 4.3. Plot showing GAMM smooths. The horizontal dashed line indicates the model intercept and the green shading highlights ROM values that are significantly greater than the model intercept, while the red shading indicates the probability of injury is not significantly greater than the model intercept.

4.5. Discussion

In this study of 93 professional pitchers, we showed that functional IR of the dominant shoulder influences the risk of a shoulder or elbow injury in-season. Specifically, we showed that extreme high (>73°) or low (<26°) measures of IR ROM may increase the risk of shoulder and elbow injuries in professional pitchers. These findings provide a promising clinical insight for the value of pre-season functional ROM on subsequent injury risk. **Figure 4.2** shows dominant functional IR versus the probability of injury. The horizontal dashed line indicates the model intercept and the green shading highlights ROM values that are significantly greater than the model intercept, while the red shading indicates the probability of injury is not significantly greater than the model intercept. As depicted, the plot takes the form of a U-shaped curve, with excessively low and high values associated with increased probability of a shoulder or elbow injury occurring in the upcoming season.

There is one other study in the literature that used multivariate analysis to develop an arm injury prediction model.[24] This study used a negative binomial regression model to predict days missed due to shoulder and elbow injuries in professional baseball pitchers. The explanatory variables used in that study were more comprehensive, including time spent in professional baseball, body mass index, workload, and previous arm injury history. The authors used a similar approach for internal validation as this study, namely ten-fold cross validation. The explanatory variable with the most similarity to those used in this study was dominant shoulder total rotational ROM, which showed a coefficient of 0.01 (95%$_{CI}$: 1.00, 1.03) (i.e., for every degree change in dominant shoulder total rotational ROM there is an increase in days missed by 1%) which was not significant as the confidence intervals spanned 1.00. The lack of literature with comparable methodologies and characteristics identifies the need for further investigation and the development of prediction models across multiple datasets to allow for continued interpretation of explanatory variables.

While the findings of this study are important, several limitations need to be acknowledged. The study is based on data from one Major League Baseball (MLB) organization, limiting the generalizability of the results to injuries sustained in-season and not those that occur during spring training. The nature of the sport, where players regularly move between teams, might influence the incidence of injuries and injury risk modifiers. The most significant limitation of this study is the small sample size combined with a low prevalence of injury in the dataset. The injury prevalence in this study was 12%, while comparable datasets used in injury risk modelling report significantly higher values.[24] Further, shoulder rotational ROM in professional pitchers is highly dependent on the pitching volume that athlete has participated in during the days leading up to the assessment.[25] Each individual was tested on arrival to spring training, but prior throwing history was not reported and unaccounted for in evaluation of the dataset. Additionally, pitching exposure is a variable that has a significant impact on injury risk and was not included in the analysis due to lack of availability. Lastly, prior shoulder or elbow injury history was not included as a covariate in this study and has been shown to be a risk modifier for future injury in other sporting domains.[26,27] Overall, the collection of more data and data sharing across more organisations would help to address these issues in future studies.

In conclusion, dominant shoulder IR that has been transformed for HT was found to be the only significant explanatory variable, with those values <26° and >73° showing an increased probability of shoulder or elbow injury in the upcoming season. The implications of this finding support the use of HT in clinical practice and screening for those who exhibit excessively high or low amounts of functional IR. Future research should continue to transform to functional ROM using HT when measuring rotational ROM and attempting to determine injury risk, along with controlling for it as a confounding variable. Incorporating other modifiable and non-modifiable explanatory variables into the model on a larger dataset with a higher injury prevalence could produce more robust results and should be explored. In addition, using pitching exposure as another explanatory variable and performing a survival regression with reference to their exposure would be a greatly bolster the inferences made on injury risk in this type of study. Lastly, due to the fluid nature of rotational ROM in the shoulder of professional pitchers, the use of time-series data to track ROM during the season may provide more robust insight into how rotational ROM influences shoulder and elbow injury prediction.

4.6. References

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CHAPTER 5: DISCUSSION AND CONCLUSIONS

The literature review conducted in this thesis has revealed that shoulder and elbow injuries are prevalent among professional baseball pitchers and have a significant impact on their career.[1–4] The lost time associated with these injuries can lead to a decline in performance, which can ultimately affect the player's prospects and earning potential.[5] Furthermore, these injuries can have deleterious consequences for the teams and the fans watching the sport, as they may not be able to witness the full potential of the player. Apart from the human impact, there is also a significant financial burden associated with shoulder and elbow injuries that cannot be overlooked.[4] The cost of medical treatment, rehabilitation, and lost revenue due to the absence of the player can be substantial for both the player and the team. Additionally, the team may have to invest in finding a replacement player, which can further increase the financial burden. Therefore, it is argued that the development of effective injury risk reduction strategies at the population level for professional baseball pitchers is a pressing matter that requires the attention of researchers.

The literature review also highlighted the need for further development of the methods used in determining shoulder and elbow injury risk modifiers. Importantly, it showed that most of the current literature has used univariate analyses with an assumption of a linear relationship between the explanatory variables and injury risk in its approach in searching for injury risk modifiers. Moreover, when studying shoulder rotational range of motion (ROM), very few researchers attempted to control for humeral torsion (HT). The reason for this is assumed to be the lack of expertise, in addition the cost associated with the equipment required to measure HT.[6] Considering this lack of controlling for a significant confounder, the literature review demonstrated that while many risk modifiers have been identified, there is yet to be a decline in shoulder and elbow injury incidence across the cohort that would indicate success. Thus, it is likely that more robust analyses using multiple explanatory variables (i.e., multivariate analysis) which do not assume linearity are a potential pathway forward in the detection of injury risk modifiers. This argument of the use of multivariate analyses is further emphasised by several papers indicating the complex nature of injuries, with many modifiable (i.e., strength, range of motion etc.) and non-modifiable (i.e., age, height, handedness, environment etc.) factors influencing the instance and mechanism that a pitcher sustains an injury.[7,8] Therefore, the overall aims of the experimental chapters in this thesis were to: (1) develop a generalised additive mixed model (GAMM) to predict HT in professional baseball pitchers; (2) develop a GAMM using shoulder rotational range of motion and humeral torsion to interpret their impact on injury risk in professional baseball pitchers in the upcoming season. The key findings of the experimental chapters in this thesis are summarised below.

5.1. Summary of Experimental Findings

Chapter 3 aimed to develop a model to predict HT from range of motion and demographic variables in professional baseball pitchers. The rationale for this study was established through the literature review, which highlighted the lack of controlling for HT as a confound due to the cost and expertise associated with its measurement. We developed two models to predict HT, including: a linear mixed effects regression model (LMER) and a GAMM, alongside a null model to provide a baseline level of prediction for comparison to the other models. The key finding of this chapter was that the 12 degrees of error in the prediction of HT was too high for either of these prediction models to be utilised effectively in a clinical setting. Although the combination of prediction models and readily available predictor variables have fewer implementation barriers and may improve the uptake of HT assessment in practice, the existing assessment methodologies using ultrasound remain the most accurate and clinically relevant, despite the known cost and time burdens.

Chapter 4 aimed to develop a GAMM to predict shoulder and elbow injury risk in professional baseball pitchers using shoulder rotational ROM measures which were transformed to “functional ROM” measures using ultrasound-measured HT. The use of a GAMM to reveal associations of functional ROM was justified in that it considers multiple explanatory variables and allows for nonlinearity to explain the relationship between them and shoulder and elbow injury risk. The final GAMM showed that functional internal rotation (IR) revealed a nonlinear effect on shoulder and elbow injury risk in the upcoming season. Participants with a relatively low or high amount of functional IR exhibited a greater probability of suffering a shoulder or elbow injury versus those with functional IR between these extremes. Although these models explained only a modest amount of the variance in injury risk, this chapter provides important insights for consideration and challenges future research to consider nonlinear techniques and HT-transformed ROMs to improve the accuracy and robustness of future injury prediction models.

5.2. Synthesis of Experimental Findings and Future Direction

5.2.1. Can we predict humeral torsion using linear or nonlinear regression models?

HT impacts shoulder rotational ROM by increasing the available external rotation whilst decreasing the available internal rotation. However, HT is difficult to assess, as it requires the use of expensive equipment and technical expertise, so is often overlooked as a clinical outcome measure and injury risk modifier. Therefore, predicting HT using regression models with easily available predictor variables could impact the clinical assessment of the throwing athlete in a profound way. **Chapter 3** showed that, at this time, the appropriate predictor variables and models chosen were unable to achieve the accurate prediction of HT within a clinically meaningful amount. The continued use of ultrasound to assess HT in a point-of-care setting is strongly encouraged to allow for greater accuracy of measurement and appropriate clinical judgement is made for the athlete.

5.2.2. *What impact does preseason functional rotational range of motion have on shoulder and elbow injury risk in the upcoming season?*

Given HT impacts shoulder rotational ROM, it requires controlling as a confounding variable in assessing injury risk when using shoulder rotational ROM as an explanatory variable. **Chapter 4** showed that, when transformed for HT, shoulder IR has a nonlinear relationship to injury risk in the upcoming season. This finding exemplifies the false assumption that injury risk is a linear phenomenon, which is often made when assessing injury risk in the current literature.

5.2.3. *What limitations were highlighted in the experiments which could impact the conclusions drawn from them?*

Firstly, the sample size of the dataset used in this study is significantly smaller than prior research aimed at developing models for HT prediction and injury risk modifier identification. The small sample size impacts our confidence in using the results more broadly (i.e., the generalisability), but both studies provide a foundation and rationale for continued data collection and further analysis of a bigger cohort to ascertain a greater level of confidence in the conclusions drawn and improve the generalisability of the models. Additionally, the small sample size affected the methods used to develop the models. In both experiments, a 5-fold cross-validation method was used to split the data into training and validation groups for hyperparameter tuning and assessing the goodness-of-fit of each iteration. Once the best models were developed there was no longer any novel data for them to be tested on, likely resulting in more optimistic results, particularly in the case of HT prediction in **Chapter 3**.

In addition to the small sample size, there were a low number of shoulder and elbow injuries that occurred in the timeframe of the study for **Chapter 4**. The low injury prevalence impacted explanatory variable selection such that a significant effort was made to reduce the ratio between the number of events and the number of explanatory variables used in the model. This meant encoding the data of the non-dominant side into an asymmetry index calculation and the removal of handedness as a non-modifiable confounding variable from the final model. Moreover, there were other explanatory variables which were not collected in the dataset that could influence the results, as they have been identified as potential injury risk modifiers in previous research. Exposure to pitching (i.e., number of practices and games/innings pitched across the timespan of the study) and prior injury history (i.e., injuries sustained to the shoulder and/or elbow prior to the beginning of the study) are two key variables that were not available at the time of data collection which could impact the inferences drawn in **Chapter 4**. As discussed in **Chapter 2**, pitching exposure also influences shoulder rotational ROM measures, with an acute decreased in shoulder IR combined with an increase in shoulder external rotation (ER). While efforts are made to reduce the impact of these changes when performing data collection (i.e., collecting the ROM measures on arrival to the facility), it is unknown how much pitching/throwing exposure each participant partook in prior to their arrival and how much this influenced their ROM measures.

5.2.4. What does the future hold for this type of research?

The biggest limitation of the experimental chapters of this thesis was the small sample size used. Therefore, future investigations involved in predicting HT and identifying injury risk modifiers should include a larger sample, resulting in a higher number of events occurring in the sample. Larger samples could be collected from multiple organisations and will allow for the inclusion of more explanatory/predictor variables in the development of nonparametric models while organically increasing the level of confidence in the generalisability of the predictions and inferences we can make from them. Pitching exposure and prior injury history are two important examples that were not included in the analysis for **Chapter 4**, both of which should be strongly considered in any future research of this nature. Additionally, given the impact pitching exposure has on shoulder rotational ROM, a future study should include the measurement of these variables at specific intervals across the course of a season. Measuring the participants over time and identification of those at risk would allow the clinicians working with the players to intervene in instances where an individual player is considered to be at heightened risk of future participation in baseball activities. A study of this nature should consider including the change in functional ROM from baseline, prior injury history, HT, non-modifiable demographic data, acute pitching exposure, chronic pitching exposure and the relationship between acute and chronic pitching exposure in their analysis.

A larger dataset, or the continued collection of new data, would also allow for the use of more sophisticated cross-validation methods to improve the generalisability of the inferences made from the results. For example, nested cross-validation is performed by holding out a proportion of the entire sample prior to hyperparameter tuning using k-fold cross-validation. This method allows the researcher to test the accuracy of prediction of the outcome variable (e.g., HT, injury) using the final model on a novel sample of the cohort, improving the confidence in our understanding and interpretation of the best-fit models. Moreover, when the research question is one of solely prediction (i.e., predicting humeral torsion or injury) and interpretation of the influence of the predictor variables is not needed, perhaps more sophisticated machine learning algorithms such as random forest, support vector machine, gradient boosting algorithms or artificial neural networks could be used in the place of the GAMM. These types of machine learning models trade-off between enhanced ability to predict an outcome (versus a GAMM), with limited ability of the researcher to interpret which variables influenced the model in facilitating the predictions.

Finally, the use of more sophisticated statistical modelling is seemingly gaining momentum as the method of choice in the broader baseball literature and has tremendous potential to enhance future research in the search for associative or causative factors of injury. Baseball has led the way in the use of “analytics” in assessing performance and player acquisition for team building. And if the same collective energy is brought to answer the questions surrounding injuries, there is great optimism that they will be answered.

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APPENDIX

Appendix 1

TRIPOD Checklist: Prediction Model Development

Section/Topic	Item	Checklist Item	Page
Title and abstract			
Title	1	Identify the study as developing and/or validating a multivariable prediction model, the target population, and the outcome to be predicted.	40
Abstract	2	Provide a summary of objectives, study design, setting, participants, sample size, predictors, outcome, statistical analysis, results, and conclusions.	41-42
Introduction			
Background and objectives	3a	Explain the medical context (including whether diagnostic or prognostic) and rationale for developing or validating the multivariable prediction model, including references to existing models.	43-45
	3b	Specify the objectives, including whether the study describes the development or validation of the model or both.	45
Methods			
Source of data	4a	Describe the study design or source of data (e.g., randomized trial, cohort, or registry data), separately for the development and validation data sets, if applicable.	46
	4b	Specify the key study dates, including start of accrual; end of accrual; and, if applicable, end of follow-up.	46
Participants	5a	Specify key elements of the study setting (e.g., primary care, secondary care, general population) including number and location of centres.	46
	5b	Describe eligibility criteria for participants.	46
	5c	Give details of treatments received, if relevant.	N/A
Outcome	6a	Clearly define the outcome that is predicted by the prediction model, including how and when assessed.	48
	6b	Report any actions to blind assessment of the outcome to be predicted.	48
Predictors	7a	Clearly define all predictors used in developing or validating the multivariable prediction model, including how and when they were measured.	46-48
	7b	Report any actions to blind assessment of predictors for the outcome and other predictors.	46
Sample size	8	Explain how the study size was arrived at.	N/A
Missing data	9	Describe how missing data were handled (e.g., complete-case analysis, single imputation, multiple imputation) with details of any imputation method.	48
Statistical analysis methods	10a	Describe how predictors were handled in the analyses.	48-51
	10b	Specify type of model, all model-building procedures (including any predictor selection), and method for internal validation.	48-51
	10d	Specify all measures used to assess model performance and, if relevant, to compare multiple models.	51
Risk groups	11	Provide details on how risk groups were created, if done.	N/A
Results			
Participants	13a	Describe the flow of participants through the study, including the number of participants with and without the outcome and, if applicable, a summary of the follow-up time. A diagram may be helpful.	52-53
	13b	Describe the characteristics of the participants (basic demographics, clinical features, available predictors), including the number of participants with missing data for predictors and outcome.	52-53
Model development	14a	Specify the number of participants and outcome events in each analysis.	53
	14b	If done, report the unadjusted association between each candidate predictor and outcome.	N/A
Model specification	15a	Present the full prediction model to allow predictions for individuals (i.e., all regression coefficients, and model intercept or baseline survival at a given time point).	54
	15b	Explain how to the use the prediction model.	N/A
Model performance	16	Report performance measures (with CIs) for the prediction model.	53
Discussion			
Limitations	18	Discuss any limitations of the study (such as nonrepresentative sample, few events per predictor, missing data).	58
Interpretation	19b	Give an overall interpretation of the results, considering objectives, limitations, and results from similar studies, and other relevant evidence.	58-59
Implications	20	Discuss the potential clinical use of the model and implications for future research.	59
Other information			
Supplementary information	21	Provide information about the availability of supplementary resources, such as study protocol, Web calculator, and data sets.	N/A
Funding	22	Give the source of funding and the role of the funders for the present study.	N/A

Appendix 2

STROBE Statement—checklist of items that should be included in reports of observational studies

	Item No.	Recommendation	Page No.
Title and abstract	1	(*a*) Indicate the study's design with a commonly used term in the title or the abstract	63
		(*b*) Provide in the abstract an informative and balanced summary of what was done and what was found	64
Introduction			
Background/rationale	2	Explain the scientific background and rationale for the investigation being reported	65-68
Objectives	3	State specific objectives, including any prespecified hypotheses	68
Methods			
Study design	4	Present key elements of study design early in the paper	69
Setting	5	Describe the setting, locations, and relevant dates, including periods of recruitment, exposure, follow-up, and data collection	69
Participants	6	(*a*) *Cohort study*—Give the eligibility criteria, and the sources and methods of selection of participants. Describe methods of follow-up *Case-control study*—Give the eligibility criteria, and the sources and methods of case ascertainment and control selection. Give the rationale for the choice of cases and controls *Cross-sectional study*—Give the eligibility criteria, and the sources and methods of selection of participants	69
		(*b*) *Cohort study*—For matched studies, give matching criteria and number of exposed and unexposed *Case-control study*—For matched studies, give matching criteria and the number of controls per case	
Variables	7	Clearly define all outcomes, exposures, predictors, potential confounders, and effect modifiers. Give diagnostic criteria, if applicable	69-72
Data sources/ measurement	8*	For each variable of interest, give sources of data and details of methods of assessment (measurement). Describe comparability of assessment methods if there is more than one group	69-72
Bias	9	Describe any efforts to address potential sources of bias	69-72
Study size	10	Explain how the study size was arrived at	69
Quantitative variables	11	Explain how quantitative variables were handled in the analyses. If applicable, describe which groupings were chosen and why	73
Statistical methods	12	(*a*) Describe all statistical methods, including those used to control for confounding	73
		(*b*) Describe any methods used to examine subgroups and interactions	73
		(*c*) Explain how missing data were addressed	73
		(*d*) *Cohort study*—If applicable, explain how loss to follow-up was addressed *Case-control study*—If applicable, explain how matching of cases and controls was addressed *Cross-sectional study*—If applicable, describe analytical methods taking account of sampling strategy	N/A
		(*e*) Describe any sensitivity analyses	N/A
Results			
Participants	13*	(a) Report numbers of individuals at each stage of study—eg numbers potentially eligible, examined for eligibility, confirmed eligible, included in the study, completing follow-up, and analysed	75
		(b) Give reasons for non-participation at each stage	N/A
		(c) Consider use of a flow diagram	
Descriptive data	14*	(a) Give characteristics of study participants (eg demographic, clinical, social) and information on exposures and potential confounders	75
		(b) Indicate number of participants with missing data for each variable of interest	73
		(c) *Cohort study*—Summarise follow-up time (eg, average and total amount)	N/A
Outcome data	15*	*Cohort study*—Report numbers of outcome events or summary measures over time	75
		Case-control study—Report numbers in each exposure category, or summary measures of exposure	
		Cross-sectional study—Report numbers of outcome events or summary measures	
Main results	16	(*a*) Give unadjusted estimates and, if applicable, confounder-adjusted estimates and their precision (eg, 95% confidence interval). Make clear which confounders were adjusted for and why they were included	76-77
		(*b*) Report category boundaries when continuous variables were categorized	N/A
		(*c*) If relevant, consider translating estimates of relative risk into absolute risk for a meaningful time period	N/A

Other analyses	17	Report other analyses done—eg analyses of subgroups and interactions, and sensitivity analyses	N/A
Discussion			
Key results	18	Summarise key results with reference to study objectives	79-80
Limitations	19	Discuss limitations of the study, taking into account sources of potential bias or imprecision. Discuss both direction and magnitude of any potential bias	80
Interpretation	20	Give a cautious overall interpretation of results considering objectives, limitations, multiplicity of analyses, results from similar studies, and other relevant evidence	80
Generalisability	21	Discuss the generalisability (external validity) of the study results	80
Other information			
Funding	22	Give the source of funding and the role of the funders for the present study and, if applicable, for the original study on which the present article is based	N/A

FIN.